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Abstract

This paper investigates the effects of macroprudential policies on bank risk through a large panel of banks operating in 61 advanced and emerging market economies. There are three main findings. First, there is evidence suggesting that macroprudential tools have a significant impact on bank risk. Second, the responses to changes in macroprudential tools differ among banks, depending on their specific balance sheet characteristics. In particular, banks that are small, weakly capitalised and with a higher share of wholesale funding react more strongly to changes in macroprudential tools. Third, controlling for bank-specific characteristics, macroprudential policies are more effective in a tightening than in an easing episode.

JEL Classification: E43, E58, G18, G28.

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1. Introduction

Prior to the global financial crisis (GFC) financial stability was mainly considered from a microprudential perspective. The aim of supervisory policy was to reduce the risk that individual institutions would fail, without any explicit regard for their impact on the financial system as a whole or on the overall economy. Lehman Brothers' default reminded us that financial stability has a macroprudential or systemic dimension that cannot be ignored. Treating the financial system as merely the sum of its parts leads one to overlook the system's historical tendency to swing from boom to bust. Nowadays, financial stability is considered from a macroprudential perspective.

However, the implementation of a new macroprudential framework for financial stability raises a number of challenges. A first challenge is the evaluation of the effectiveness of macroprudential policies, especially when more than one tool is activated. Moreover, effectiveness should be analysed with respect to the specific goal that macroprudential policies are designed to achieve; that is, to increase the resilience of the financial system, or, more ambitiously, to tame financial booms and busts. At the moment, the evidence is mixed and most research focuses on analysing the impact of macroprudential tools on bank lending (as an intermediate target), not directly on bank risk (the limitation of which is the ultimate goal). For instance, recent evidence suggests that debt-to-income ratios and, probably to a lesser extent, loan-to-value ratios are comparatively more effective than capital requirements as tools for containing credit growth (Claessens et al, 2014). Indeed, the recent activation of the Basel III countercyclical capital buffer to risk-weighted domestic residential mortgages in Switzerland, though having had some effect on mortgage pricing, seems to have had little impact on credit extension (Basten and Koch, 2015). But the main goal of the Basel III buffers is to increase the resilience of the banking system, not to smooth the credit cycle. Restraining the boom is perhaps no more than a welcome, potential side effect (Drehmann and Gambacorta, 2012).

A second challenge pertains to the varied nature of macroprudential objectives and instruments. In this area, there is no one-size-fits-all approach. Which tools to use, how to calibrate them and when to deploy them will all depend on how the authorities view the vulnerabilities involved and how confident they are in their analysis. The legal and institutional setup will also be relevant. A given instrument's effects depend on a variety of factors, which have to be assessed against the chosen objective. Some instruments may work better to achieve the narrow aim of increasing financial system resilience rather than the broader aim of constraining the cycle. For instance, countercyclical capital buffers aim to build cushions against banks' total credit exposures, whereas loan-to-value ratio caps only affect new borrowers (and usually only those that are highly leveraged). This argues in favour of capital buffers if the objective is to improve overall resilience. However, loan-to-value ratios may be more effective if the aim is to curb specific types of credit extension.

Third, most macroprudential policies aim at containing systemic risk, a type of risk that is by nature endogenous. By using macroprudential tools, policymakers aim at limiting bank risk-taking and the probability of the occurrence of a financial crisis. This means that – ideally – we should also be interested in how these policies influence a bank's contribution to system-wide risk. Measurement of systemic risk is, however, still rudimentary, although some concepts have been developed (measures such as CoVaR, stress testing and Shapley values).

A first step could be to evaluate how macroprudential tools impact specific measures of bank risk, such as the expected default frequency (EDF) or the Z-score. The calculation of the EDF indicator requires bank issuance of equity on the stock market, while the Z-score is an indicator of the probability of default which relies on balance sheet variables.

This paper complements other studies on the effectiveness of macroprudential policies.[1] Its main contribution is to analyses the effectiveness of such policies on bank risk in a comprehensive way, exploiting the cross-sectional dimension among countries. Interestingly, the more advanced economies tended to ignore the macroprudential dimension in the run-up to the crisis. Emerging market economies (EMEs) were generally better aware of the need to think about the financial system as a whole, and more willing to intervene in response to evidence of a build-up of imbalances and risks (Figure 1). All this means that it is necessary to pool information for a large number of banks operating in both advanced countries and EMEs, and to control for different institutional setups and time-specific factors affecting the risk-taking channel. In other words, pooling information regarding countries with different experiences in the use of macroprudential tools greatly reduces concerns about possible omitted variables (Demirguc-Kunt et al, 2013).

Using information for 3,177 banks operating in both advanced economies and EMEs over the period 1990–2012, we find that macroprudential tools – both those focusing on dampening the cycle (ie loan to value ratios, reserve and currency requirements) and those specifically designed to enhance banks' resilience (ie capital requirements) – have a significant impact on bank risk. We also find that the responses to changes in macroprudential tools differ among banks, depending on their specific balance sheet characteristics. In particular, banks that are small, weakly capitalised and with a higher share of wholesale funding react more strongly to changes in macroprudential tools. Finally, macroprudential policies are more effective in a tightening than an easing cycle.

The remainder of this paper is organised as follows. The next section discusses how macroprudential policies can impact bank risk. Section III describes the identification strategy and data used in our analysis, while Section IV and V present the main results and robustness checks. The last section summarises our main conclusions.

2. Macroprudential policy and bank risk

Following a widely accepted definition, "macroprudential policies are designed to identify and mitigate risks to systemic stability, in turn reducing the cost to the economy from a disruption in financial services that underpin the workings of financial markets - such as the provision of credit, but also of insurance and payment and settlement services" (FSB/IMF/BIS, 2009). However, providing a framework for the relationship between macroprudential policies and systemic risk is not straightforward. The need for macroprudential policies arises from two dimensions of systemic risk: the time and cross-sectional dimensions.

The time dimension represents the need to constrain financial booms (Borio, 2014). Such financial booms can originate from both the supply and demand sides of agents, and financial

[1] For an overview of the existing empirical evidence on the effectiveness of macroprudential policies see, amongst others, Claessens (2014).

intermediary behaviour. For example, the amplification mechanism known as "financial accelerator" is mainly related to the demand side (Claessens et al, 2014). But other mechanisms are related to the supply side, as in the model of Adrian and Shin (2010, 2014), where an initial positive shock that boosts the value of a bank's assets, such as loans and securities, could induce a further increase in debt if the bank targets a certain leverage ratio. Banks' decisions on leverage and the composition of assets and/or liabilities could make them more vulnerable to future negative shocks through balance sheet mismatches.

The second feature of systemic risk is its cross-sectional dimension, which is mainly related to the interconnectedness of financial institutions. This aspect became the focus of policy discussion after the GFC as specific shocks to some institutions were heavily amplified by spreading across financial markets and countries. The new Basel III regulatory framework, for instance, which targets systemically important financial institutions (SIFI) with specific capital surcharges, aims to reduce negative externalities stemming from interconnectedness.

The risk-taking behaviour of banks, thus, could be mitigated by the active use of macroprudential policies. For instance, capital-based instruments, such as capital conservation buffers, would allow institutions to accumulate capital in good times, which could then be used to absorb losses in stress periods. Similarly, the countercyclical capital buffer could be actively used to "achieve the broader macro-prudential goal of protecting the banking sector from periods of excess credit growth." (BCBS, 2010, pp 5). In addition, provisioning requirements, such as the dynamic provisioning tool used in Spain, also require banks to adjust the total amount of loss provisions when their profits are growing, with the aim of being able to draw on these provisions during an economic downturn. Therefore, the collective use of capital-based requirements could mitigate bank risk by requiring higher buffers during an upturn. Bank risk could be further mitigated by the use of other macroprudential tools during an upturn. For instance, increasing liquidity requirements and imposing stringent currency instruments could minimise bank risk emanating from repricing and liquidity gaps, as well as exchange rate fluctuations. Therefore, single or multiple uses of macroprudential instruments are expected to have an impact on the EDF or Z-score of banks, two alternative measures or bank risk used in this study.

Besides the direct effect of macroprudential tools on bank risk, monetary policy also has an impact on risk-taking and financial stability (Gambacorta, 2009; Borio and Zhu, 2014; Altunbas et al, 2014; Dell'Ariccia et al, 2010). A prolonged period of low interest rates could impact risk-taking in two different ways. The first is through the search for yield (Rajan, 2005). Low interest rates may increase incentives for asset managers to take on more risks for contractual, behavioural or institutional reasons. For example, in 2003–2004, many investors shifted from low-risk government bonds to higher-yielding but also to riskier corporate and EME bonds. A similar mechanism was detected in the theoretical model designed by Dell'Ariccia et al (2010): monetary easing leads to a reduction in the interest rate on bank loans, which, in turn, reduces a bank's gross return, conditional on its portfolio. This reduces the bank's incentive to monitor its loans, and the real yield on safe (monitored) assets, thus banks will typically increase their demand for risky assets.

The second way in which low interest rates could encourage banks to take on more risk is through their impact on valuations, incomes and cash flows.[2] A reduction in the policy rate boosts asset and collateral values, which in turn can modify bank estimates of probabilities of default, losses given default and volatilities. For example, by increasing asset prices, low interest rates tend to reduce volatility and thus risk perceptions: since a higher stock price increases the value of equity relative to corporate debt, a sharp increase in stock prices reduces corporate leverage and could thus decrease the risk of holding stocks.[3] This example can be applied to the widespread use of Value-at-Risk methodologies for economic and regulatory capital purposes (Danielsson et al, 2004). As volatility tends to decline in rising markets, it releases the risk budgets of financial firms and encourages position-taking. A similar argument is made in the model of Adrian and Shin (2009), who stress that changes in measured risk determine adjustments in bank balance sheets and leverage conditions, and, in turn, amplify business cycle movements.[4]

Macroprudential tools could, in principle, be used to moderate the risk-taking incentives arising from monetary policy decisions. For instance, Igan and Kang (2011) argue that the impact of a tightening of monetary policy on defaults can be contained by having in place conservative limits on debt-to-income (DTI) ratios. On the other hand, macroprudential measures, such as limits on LTV ratios, can reduce vulnerabilities under the condition that accommodative monetary policy is driving up asset prices. Additionally, higher capital requirements (including countercyclical) or tighter leverage and liquidity ratios may help contain increases in bank risks in response to expected lax monetary policy (see Farhi and Tirole, 2012; IMF, 2013). To complement the theoretical discussions outlined above and individual country studies, the analysis in this paper controls for monetary policy conditions and a broader set of country- and bank-specific characteristics.

3. Model, identification strategy and data

The baseline empirical model is given by the following equation, adapted from Altunbas et al (2014):

$$\begin{aligned}\Delta Risk_{i,k,t} = \alpha \Delta Risk_{i,k,t-1} + \beta \Delta EDF\_NF_{k,t} + \gamma MP_{k,t} + \\ + \psi\ MC_{k,t} + \lambda BSC_{i,k,t-1} + \theta_i + \kappa_{k,t} + \varepsilon_{i,k,t}\end{aligned} \tag{1}$$

2 This is close in spirit to the familiar financial accelerator, in which increases in collateral values reduce borrowing constraints (Bernanke et al, 1996). Adrian and Shin (2009) claim that the risk-taking channel differs from and strengthens the financial accelerator because it focuses on amplification mechanisms created by financing frictions in the lending sector. See also Borio and Zhu (2014).

3 For this reason, the link between asset prices and asset price volatility is sometimes described as the leverage effect. See, amongst others, Pagan and Schwert (1990) and the studies cited in Bollerslev et al (1992).

4 Risk-taking may also be influenced by the communication policies of a central bank and the characteristics of policymakers' reaction functions. For example, a high degree of central bank predictability with regard to future policy decisions can reduce market uncertainty and thus lead banks to take on more risks. Moreover, agents' perception that the central bank will ease monetary policy in the event of adverse economic outcomes could lower the probability of large downside risks, thereby producing an insurance effect. For this reason, Diamond and Rajan (2012) argue that, in order to diminish banks' incentive to take on liquidity risk, monetary policy should be kept tighter in good times than strictly necessary based on current economic conditions,.

with i=1,..., N , k= 1, ...,K and t=1, ..., T, where i is the bank, k is the country and t is time. Table 1 reports the summary statistics for the variables used and the relevant sources. The final database includes 3,177 banks headquartered in 61 countries.[5] More information at the country level is provided in Annex A.

In the baseline equation (1), the annual change of the risk measure (Δ*Risk*) for bank *i*, headquartered in country *k,* in year *t*, is regressed on its own lag and *EDF* change for the non-financial sector in country *k* (Δ*EDF_NF*). This variable aims at filtering out the effects of changes in the market price of risk due to the business cycle. *MP* indicates the change in the macroprudential tool, which could be the change in an aggregate index, as in Cerutti et al (2016), or a complete vector of macroprudential tools. *BSC* and *MC* represent, respectively, additional bank-specific characteristics and macro variables that are introduced to disentangle the risk-taking channel from other mechanisms at work. In particular, the vector MC includes a measure for the monetary policy stance (DIFF, the difference between the real interest rate and the natural rate) and the growth rate of nominal GDP (ΔGDP).[6] We also include time invariant bank fixed effects (θ_i) and a dummy variable ($\kappa_{k,t}$) that takes the value of 1 in those specific years in which countries experienced a banking crisis and zero elsewhere (Valencia and Laeven, 2012).

3.1 Measurement of bank risk

By setting macroprudential tools, policymakers aim to limit bank risk-taking and the probability of the occurrence of a financial crisis. This means that – ideally – we should measure how macroprudential policies influence a bank's contribution to system-wide risk. Measurement of systemic risk is, however, still rudimentary, although some concepts have been developed (CoVaR, stress testing and Shapley value measures). A compromise could be to evaluate how macroprudential tools impact specific measures of bank risk.

In the baseline model, the *dependent variable* is given by the change in the EDF (Δ*EDF*), representing the probability that a bank will default within a given time horizon (typically one year). *EDF* is a well-known, forward-looking indicator of risk, computed by Moody's KMV, which builds on Merton's model to price corporate bond debt (Merton, 1974). The *EDF* value, expressed as a percentage, is calculated by combining banks' financial statements with stock market information and Moody's proprietary default database. We also checked the robustness of the results by using change in the *Z-score* as an alternative measure of bank risk.[7] We mitigate the effects of outliers by dropping the first and the last percentile of the

[5] We control for mergers and acquisitions in the following way. If a bank A and a bank B are merged in a bank C, we consider bank A and bank B as different financial intermediaries until the date of the merger and then we include a new bank C. In case a bank D acquires a bank E, we include Bank E in the database until the date of the acquisition, and we drop the year-observation for bank E in which the acquisition took place. After excluding the presence of outliers, excluding information in the first and last percentile of the distribution, 20,870 observations and 3,177 banks remained.

[6] Similar results (not reported) are obtained by including in the specification both the growth rate of real GDP and the inflation rate.

[7] The Z-score can be summarised as Z=(k+ROA)/σ_{ROA}, where k is equity capital as percent of assets, ROA is the average after-tax return as a percent of assets, and σ_{ROA} is the standard deviation of the after-tax return on assets, as a proxy for return volatility. The Z-score measures the number of standard deviations a return realisation has to fall in order to deplete equity, under the assumption of normality of bank returns. A higher Z-score corresponds to a lower upper bound of insolvency risk. A higher z-score implies therefore a lower probability of insolvency risk. For an application, see amongst others, Laeven and Levine (2009).

distribution of the variables. Figure 2 shows that the cross-sectional dispersion of banks' *EDFs* and *Z*-scores (both measured by means of the coefficient of variation) is not concentrated in the period of the GFC. This means that there were already significant differences in bank risk at the cross-sectional level prior to the crisis. Interestingly the cross-sectional dispersion of the *Z*-score is also very high in relation to the early 1990s' recession and associated banking crisis.

In Table 2, banks are grouped depending on their specific risk position, using one-year *EDF* values. For the bank-specific characteristics, we use bank-level data from BankScope, a commercial database maintained by Fitch and Bureau van Dijk. A "high-risk" bank has the average *EDF* of banks included in the tenth decile (ie in the 10% of the riskier banks with an average *EDFH* equal to 7.4%); a "low-risk" bank has the average *EDF* of the banks in the first decile (*EDFL* is equal to 0.07%). The first part of the table shows that high-risk banks are less strongly capitalised. The lower level of capitalisation appears to be consistent with the higher perceived risk of these banks. Additionally, low-risk banks make relatively more loans than high-risk banks, and are more efficient (have a lower cost-to-income ratio).

Bank profitability, measured by Return on Assets (ROA), is higher and more stable for low-risk banks. This result is probably due to the inclusion of the GFC period in the sample. The coefficient of variation of the ROA, calculated using information for the four quarters ahead, for low-risk bank is indeed half (one quarter) with respect to high-risk banks, considering the EDF (*Z*-score) as a measure of risk.

It is worth noting that banks with a lower *Z*-score are more risky, while banks with a lower EDF are less risky. To compare the signs of the coefficients in the regressions, we therefore multiply the *Z*-score by -1. Using this approach, a higher level of the two indicators (*Z*-score and *EDF*) is always associated with more risky banks.

3.2 Macroprudential policy indicators

The construction of macroprudential policy indicators involves a number of steps. First, we consider an aggregate index that allows us to evaluate the overall effectiveness of macroprudential tools when more than one measure is activated. This aggregate index represents a very rough approximation because macroprudential tools may be very different in nature. For example, we may need to consider a case where the minimum loan to value ratio was increased while, contemporaneously, reserve ratios were reduced. To deal with this kind of situation, we first consider a dummy that takes the value of +1 if a given macroprudential tool was tightened and -1 if it was eased, leaving zero elsewhere. Then, following Kuttner and Shim (2013), we calculate an aggregate macroprudential indicator ($MP\_index_{k,t}$) that sums up all the different dummies for the various macroprudential tools. This means that, if multiple actions in the same direction are taken within a given year, the variable could take on the values of 2 or –2, or even 3 and –3. It also means that a tightening action and a loosening action taken within the same year could cancel each other out. This indicator weights each tool in the same way and will be considered in our baseline regression.

Second, we recognise that the macroprudential toolkit tends to be large, as it combines an array of different instruments. In particular, we distinguish them according to the following five categories: a) capital-based instruments; b) liquidity-based instruments; c) asset-side instruments; d) reserve requirements; and e) currency requirements. Table 3 provides an overview of these categories (with further information in Annex B).

Third, the purpose of the various policies could differ. For instance, some instruments are intended to increase directly the financial sector's resilience, while others focus on dampening the cycle as an intermediate target. In that respect, the effects of specific macroprudential tools on credit growth and bank risk can be different. Claessens et al (2014) distinguish between the goals and the types of policy that are commonly used. Macroprudential tools with the main objective of enhancing the financial sector's resilience include countercyclical capital requirements, leverage restrictions, general or dynamic provisioning, and the establishment of liquidity requirements, among others. Within the category of macroprudential tools aimed at dampening the credit cycle, Claessens et al (2014) include changes in reserve requirements, variations in limits on foreign currency mismatches, cyclical adjustments to loan-loss provisioning, and margins or haircuts. Other macroprudential policy aims include reducing the effects of contagion or shock propagation from SIFIs or networks. This group might also include policies, such as capital surcharges linked to systemic risk, restrictions on asset composition or activities.

Using the categorisation presented in Claessens et al (2014), we classify policies according to their purpose. In particular, policies to dampen the cycle – ie those used by authorities countercyclically to dampen an expected credit boom or credit crunch – are identified with by term *cyclical* (we refer to the categories (c), (d) and (e) in Table 3). Macroprudential tools with a more structural objective, which are intended to increase the resilience of the financial sector (such as capital, liquidity or provisioning requirements), are identified with by the term *resilience* (categories (a) and (b) in Table 3).

The chart pie on the left-hand side of Figure 3 splits the different types of macroprudential policy adopted in the period 1990–2014. Interestingly, only one quarter of policies are aimed at improving the resilience of the financial sector using capital, liquidity of provisioning requirements (slices in blue colour). By contrast, the vast majority have the purpose of dampening the cycle – ie those used by the authorities countercyclically to dampen an expected credit boom or credit crunch. More than half are represented by changes in reserve requirements.

Finally, we split the changes in macroprudential tools into easing and tightening cases. In this way, we can verify the asymmetric effects of each tool. The chart pie on the right-hand side of Figure 3 shows that in three quarters of cases macroprudential tools were tightened. The dummy MP_easing (MP_tightening) takes a value of 1 if the macroprudential tool was eased (tightened) in a given year and zero elsewhere. This specification is particularly important to check our results against the existing literature. Cerutti et al (2016), for example, find some evidence of the asymmetric impact of macroprudential policies, claiming that those policies seem more effective when credit growth rates are very high, but have a less positive impact during busts. Similarly, Claessens et al (2014) find that macroprudential policies help mitigate asset growth, with the effects largely present during the boom (implying that the tightening measures are more effective). Finally, Kuttner and Shim (2013) find that three of the four macroprudential policies analysed in their study have statistically significant effects on housing credit when measures are tightened but not loosened. However, they find similar but weaker asymmetric responses when they assess the impact of macroprudential policies on house prices.

3.3 Bank-specific characteristics

In order to discriminate between loan supply and demand movements, the bank lending channel literature has focused on cross-sectional differences across banks. This strategy relies on the hypothesis that certain bank-specific characteristics (for example, bank size, liquidity, capitalisation and funding composition) only influence loan supply while a bank's loan demand is largely independent of these factors. Broadly speaking, this approach assumes that, after a monetary tightening, the drop in the total availability of funding, which affects banks' ability to make new loans or their ability to shield their loan portfolios, differs among banks.

Drawing on this literature, we analyse macroprudential tools in the same way as monetary policy changes. Using the BankScope database, we therefore include four bank-specific characteristics that could influence bank supply shifts in the case of macroprudential policy changes. The first three are: bank size, proxied by the logarithm of a bank's total assets (*SIZE*), the liquidity ratio (*LIQ*) and the capital to asset ratio (*CAP*). These give insightful information, not only on banks' ability to insulate loan supply from monetary and macroprudential shocks (Kashyap and Stein, 2000; Kishan and Opiela, 2000; Gambacorta, 2005) but also control for "too big to fail" considerations, differences in business models and capital regulation effects. The fourth indicator is the share of deposits over total liabilities (*DEP*), a measure of a bank's contractual strength. Banks with a large amount of deposits will adjust their deposit rates by less (and less quickly) than banks whose liabilities are mainly composed of variable rate bonds that are directly affected by market movements (Berlin and Mester, 1999). Intuitively, this should mean that, in view of the presence of menu costs, it is more likely that a bank will adjust its terms for passive deposits if the conditions relating to its own alternative form of refinancing (ie bonds) change. Moreover, a bank will refrain from changing deposit conditions because, if the ratio of deposits to total liabilities is high, even small changes to their price will have a substantial effect on total interest rate costs. By contrast, banks that use relatively more bonds than deposits for financing purposes come under greater pressure because their costs increase contemporaneously with market rates (and to a similar extent). Finally, the ratio of bank deposits over total liabilities is also influenced by the existence of deposit insurance, which makes this form of funding more stable and less exposed to the risk of a run. Acharya and Mora (2015) report that banks may actively manage the deposit to total funding ratio by changing deposit rates.

To draw a parallel with the bank lending channel literature, it is interesting to investigate whether the responses to macroprudential shocks differ by type of bank. To test for this, we introduce interactions terms that are the products of a macroprudential indicator and bank-specific characteristics ($MP_{k,t} * BSC_{i,k,t-1}$):

$$\begin{aligned} \Delta Risk_{i,k,t} &= \alpha \Delta Risk_{i,k,t-1} + \beta \Delta EDF\_NF_{k,t} + \gamma MP_{k,t} + \psi\ MC_{k,t} + \lambda BSC_{i,k,t-1} + \\ &+ \delta\ MP_{k,t} * BSC_{i,k,t-1} + \theta_i + \kappa_{k,t} + \varepsilon_{i,k,t} \end{aligned} \tag{2}$$

Similarly, with the approach used by the bank lending channel literature, the relevant test is on the significance of δ. Broadly speaking, this approach assumes that after a monetary tightening episode (macroprudential tightening in our case), the ability to shield loan portfolios is different across banks. In particular, small and less strongly capitalised banks, which suffer from a high degree of informational frictions in financial markets, face a higher cost in raising non-secured deposits and are forced to reduce their lending by more than other banks; illiquid banks have fewer options for shielding themselves from the effect of a prudential policy tightening on lending simply by drawing down cash and securities. Therefore, this literature does not analyse the macroeconomic impact of the "bank lending channel" on loans but asserts the existence of such a channel, based on the fact that different responses of lending supply among banks are detected. All bank-specific characteristics have been "demeaned" so that the coefficients λ and δ can be considered to be the effects on the average bank.

3.4 Endogeneity issues

One possible limitation of the suggested empirical strategy is that, in principle, the situation of the banking sector could also have an impact on macroprudential policy decisions. In order to mitigate endogeneity problems, we use the dynamic Generalised Method of Moments (GMM) panel methodology to obtain consistent estimates of the relationship between macroprudential policy and bank risk. This methodology was first described by Holtz-Eakin et al (1988), and Arellano and Bond (1991), and further developed by Blundell and Bond (1998). The use of this methodology reduces any endogeneity bias that may affect the estimation of the regression parameters. It also takes into account the heterogeneity of the data caused by unobservable factors affecting individual banks.

We use the instruments as defined by Blundell and Bond (1998). According to these authors, the exogenous variables, transformed in first differences, are instrumented by themselves, while the endogenous regressors (also transformed in first differences) are instrumented by their lags in levels.[8] As a final precaution, we consider all bank-specific characteristics at *t-1*.

4. Results

The main results are reported in Tables 4 to 7. The S-GMM estimator ensures efficiency and consistency, provided that the residuals are not subject to serial correlation of order two (AR(2) test), and that the instruments used are valid (Hansen test). Neither test (as reported at the bottom of each table) should fail to reject the null hypothesis.[9]

Table 4 presents the baseline regression results of specifications (1) and (2) using the *MP_index*. The table is split into two parts: the first two columns use the EDF as dependent

[8] This approach has been applied to other areas of research in which the model was affected by possible endogeneity biases. For instance, Blundell and Bond (1998) use it to estimate a labour demand model while Beck et al (2000) apply it to investigate the relation between financial development and economic growth.

[9] The consistency of the S-GMM estimator depends on the validity of the assumption that the error terms do not exhibit serial correlation and on the validity of the instruments. To address these issues, we use two specification tests suggested by Arellano and Bond (1991), and Blundell and Bond (1998). The first is a Hansen test of over-identifying restrictions, which tests the overall validity of the instruments by analysing the sample analogue of the moment conditions used in the estimation process. The second test examines the hypothesis that the error term ε_{ikt} is not serially correlated. We test whether the differenced error term is second-order serially correlated (by construction, the differenced error term is probably first-order serially correlated even if the original error term is not). Failure to reject the null hypotheses of both tests should give support to our models.

variable, while the last two columns use the Z-score. To make results comparable, we multiply the Z-score by -1. In this way larger values of both the EDF and Z-score indicate higher risk.

The coefficients on the *MP_index* are negative and significant, indicating that a tightening (easing) of macroprudential policies reduces (increases) bank risk. All coefficients for bank-specific indicators are highly significant for the EDF and Z-score in our baseline model.

The interaction terms between the *MP_index* and bank specific characteristics in column (2) and (4) indicate that the impact of macroprudential policies on bank risk is stronger for banks that are weakly capitalised, smaller, with low liquidity buffers and with a higher incidence of wholesale funding (fewer deposits). These results are in line with Gambacorta and Shin (2016): well capitalised banks are considered as less risky by the market and pay less – other things being equal – on their debt funding. Moreover, banks with a large proportion of deposits are considered safer because of the presence of deposit insurance.

Figure 4 summarises the effects of macroprudential tools for banks with different levels of capital. The estimates roughly imply that a tightening of macroprudential tools leads to a decline in the expected default probability of around 0.7 percent for the average bank. The effect is higher for weakly capitalised banks (−0.9 percent) than for strongly capitalised ones (−0.4 percent), which have better access to markets for non-reservable liabilities. It is worth remembering that testing the null hypothesis that macroprudential policies effects are equal among banks with different capital ratios is identical to testing for the significance of the interaction between capital and the macroprudential policy indicator (see the coefficient on $MP\_index_t*CAP_{t-1}$ in the second column of Table 4). Similar results are detected considering the Z-score as indicator of bank risk (see Figure 4 and the fourth column of Table 4).

The analysis of the other control variables also provides interesting insights. The positive value of the lagged dependent variable indicates persistence in the adjustment process of risk. Changes in the EDF of the non-financial sector are positively linked to banks' EDF and Z-scores. This implies that the risks affecting financial firms are driven by broad movements in risk that are related to the overall behaviour of the economy (captured by non-financial sector risk). As indicated by the risk-taking channel, the monetary policy indicator (the difference between the real interest rate and the natural rate) is negatively correlated with bank risk. This means that a less restrictive monetary policy is associated with a higher level of bank risk. The state of the business cycle (growth rate of nominal GDP) is also negatively correlated with changes in bank risk-taking. However this effect is statistically significant only when the Z-score is used as a risk–taking measure.

Table 5 presents the results of model (2) where the *MP_index* is divided in two separate indices, one for macroprudential tools aimed at dampening the credit cycle (*MP_cyclical index* for categories (c), (d) and (e) in Table 3) and another one for macroprudential tools whose main objective is to enhance the financial sector's resilience (*MP_resilience index* for categories (a) and (b) in Table 3).

We also find in this case the expected negative sign on the two macroprudential indices: a tightening (easing) of macroprudential policies reduces (increases) risk for the average bank (remember that all bank-specific characteristics are demeaned). The interaction of the two macroprudential indices with bank-specific characteristics confirms that the impact of macroprudential policies on bank risk is stronger for banks that are weakly capitalised, smaller, with low liquidity buffers and with a higher incidence of wholesale funding. Interestingly, the magnitude of the interaction terms is greater for macroprudential tools whose main objective is to enhance the financial sector's resilience. This is not surprising as these tools (capital and liquidity requirements) have a more direct impact on banks' credit supply.

In the first column of Table 6, we extend the analysis in two ways. First, we consider the possibility of asymmetric effects for a tightening and an easing of macroprudential policies. Second, we consider the five macroprudential categories described in Table 3. We find, in general, the expected signs. In the majority of cases, macroprudential tightening has a negative and significant impact on bank-risk, while easing has a positive effect. Similar results are obtained in the first column of Table 7 where we use changes in the Z-score as dependent variable rather than changes in the EDF. There are, however, cases (depending on the measure of bank risk used) in which some macroprudential tools do not produce significant effects on a bank's risk. These cases have to be further investigated because the effect may not be homogenous among banks, ie affecting some banks with certain specific characteristics more than others.

Another finding is that the effects are not always symmetric in magnitude for the average bank. However, the difference between the coefficients *MP_easing* and *MP_tightening* are in most cases not statistically significant. There is a slight tendency for asset class measures (such as changes in LTV or debt to income ratios) and, to some extent, currency tools to be more effective in an easing than in a tightening. On the contrary, reserve requirements seem more effective in a tightening but only when EDF is considered as a bank risk indicator. Moreover, in this case, the asymmetry needs further analysis by considering how banks with different characteristics react to changes in macroprudential tools.

To this end, we extend the model by inserting interaction terms that are the products of macroprudential indicators and bank-specific characteristics (see equation (2)). As pointed out in section 3, this is similar to the approach taken by the bank lending channel literature, which identifies shifts in the supply of loans by considering a different reaction of banks to monetary policy shocks depending on their characteristics. In columns (II) to (V) of Table 6, we report estimation results for equation (3) for each bank-specific characteristic, one at a time. Table 7 does the same but considers the Z-score as a dependent variable. Three main results emerge.

First, many interaction terms (17 out of 40 for EDF; 24 out of 40 for Z-score) are statistically significant, indicating that macroprudential policies have heterogeneous effects across banks. Table 6 results indicate that the significance and sign of the coefficients for the five groups of macroprudential tools in specifications (II) to (V) are consistent, in general, with those expected from theory.

In particular, banks that are small, weakly capitalised and with a low proportion of deposit funding (more wholesale funding) react more strongly to macroprudential shocks. Given that small and less strongly capitalised banks suffer from a higher degree of informational friction in financial markets, and face higher costs in raising non-secured deposits, then macroprudential measures would be expected to have a larger impact on their risk-taking capacity. Liquidity does not seem to affect significantly a bank's risk response to macroprudential changes, with the notable exception of a tightening of reserve requirements, against which liquid banks seem perfectly insulated.

Third, controlling for bank characteristics, macroprudential tools are more effective in a tightening than in an easing episode. For instance, in Table 6 for EDF, 11 out of 20 interaction terms are significant at a conventional level for tightening measures, while it is 6 out of 20 for easing interactions. A similar pattern of interaction terms exists for the Z-score in Table 6 (14 out of 20 for tightening; 10 out of 20 for easing). Heterogeneity is particularly evident when considering banks with a different degree of leverage, in particular for the Z-score and deposit ratio for EDF results. The higher effectiveness of tightening measures when bank-specific interactions are considered is in line with Claessens et al (2014), Cerutti et al (2016) and McDonald (2015).

5. Robustness checks

In this section, we perform a number of tests to check the robustness of our results to: i) the presence of possible heterogeneity in the effectiveness of macroprudential tools caused by different stages of economic and financial development across countries; ii) the effects of the GFC in the last part of the sample; iii) the effects of global macroeconomic and financial conditions; and iv) possible limits in our data coverage.

Regarding possible difference in the effectiveness of macroprudential tools across jurisdictions, we divided the sample (3,177 banks and 20,870 observations) between advanced economies (2,286 banks and 15,144 observations) and EMEs (891 banks and 5,756 observations).[10] This test is particularly relevant as the data for EMEs typically contain more gaps and are only available for a limited number of financial intermediaries. The results reported in Tables C1-C4 in Annex C indicate that in both groups of countries, macroprudential policies have a significant impact on banks' risk-taking. Figure 5 reports the average effect of a macroprudential policy tightening, distinguishing those tools aimed at dampening the cycle (Cyclical) from those whose main objective is to enhance the financial sector's resilience (Resilience). For example, on average, macroprudential tightening reduces the probability of a bank's default by 0.35% (first histogram in the left-hand panel). The effect is higher in advanced economies (-0.47%) than in EMEs (-0.15%). Similar effects can be detected in terms of Z-scores.

In addition, risk for banks that are small, less well capitalised and with a higher share of wholesale funding reacts more strongly to changes in macroprudential tools aggregated into an MP index (Tables C1 and C3). In both groups of country, the tools that primarily aim at enhancing resilience (MP resilience index) and those that focus above all on taming financial booms and busts (MP_cyclical index; see Tables C2 and C4) have an impact on bank risk.

In the second robustness test, we limit our analysis to the pre-crisis period. Table C5 and C6 report the results for the baseline regressions estimated over the period 1990–2007. Even after losing one third of the observations, the results are qualitatively very similar.

In the third test, we add to the equations a complete set of time dummies to capture changes in global macroeconomic and financial conditions. The results reported in Tables C7 and C8 remains very similar. The robustness of the results is also confirmed when we include in the specification a full set of country*time fixed effects (and drop the macroeconomic controls): sign and significance of the interaction terms between macroprudential index and bank-specific characteristics remain qualitatively very similar (see Table C9).

10 The distinction between advanced economies and EMEs is based on the 86th Annual report of the BIS, p. vii. Advanced economies are highlighted in italics in Annex A while the remaining economies, which are considered to be EMEs, are not.

The above results may also be influenced by differences in the intensity of bank supervision, unrelated to macroprudential policies, which could have an impact on the amount of risk undertaken (Beltratti and Stulz, 2012). In a fourth test, we therefore verify whether more permissive legislation on bank activities could have led financial intermediaries to take more risks. Following Karolyi and Taboada (2015), we construct a Regulatory Strength Index (RSI) using the logarithm of the sum of four indices that measures the quality of bank regulation from Barth et al (2013). [11] As the index is available only for the period 1999–2012, the number of observations drops to 16,615. Tables C10 and C11 report the results including this indicator. We also report, for completeness, the coefficient of the crisis dummy $\kappa_{k,t}$ (used in all specifications) which takes the value of 1 in those specific years during which countries experienced a banking crisis and zero elsewhere (Valencia and Laeven, 2012). Interestingly, the dummy that captures regulatory strength is negatively correlated with both measures of bank risk. At the same time, the dummy the captures the crisis picks up the effect of financial distress on banks. All other results remain practically unchanged.

The use of the EDF measure as dependent variable for risk reduces the number of observations because this indicator is available only for a limited number of banks. As a final robustness check, we run the baseline regressions on a larger sample of financial intermediaries using only the Z-score. This allows us to increase the number of banks from 3,177 to 17,963, and the number of observations from 20,870 to 115,611. The results reported in Table C12 are qualitatively very similar.

6. Conclusions

The global financial crisis highlighted the importance of financial stability, and hence the need for macroprudential policies to achieve that objective. Particularly during and after the crisis, many countries began to implement various macroprudential tools to deal with financial vulnerabilities and mitigate systemic risk. Recent theoretical and empirical literature has focused on various aspects of macroprudential policies, including the effectiveness of those policies and their implications for business and financial cycles.

This paper fills an existing gap in the literature. In particular, while other studies focus on the impact of such policies on bank lending, our paper analyses their effectiveness on bank risk. We do this in a comprehensive way, exploiting the cross-sectional dimension of countries for a large panel of banks operating in 61 advanced economies and emerging market economies over the period ranging from 1990 to 2012.

The paper presents three main results. First, it provides evidence suggesting that macroprudential tools are effective in modifying bank risk-taking. Second, the responses to

[11] The indices and the question numbers (and their range) in Barth et al (2013) are as follows: I.IV: Overall Restrictions on Banking Activities (3-12); IV.III Capital Regulatory Index (0-10); V.I Official Supervisory Power (0-14); VII.VI Private Monitoring Index (0-12). The RSI could in principle take a value ranging from 3 (minimum regulation) to 48 (most stringent regulation). Barth et al (2013) provide surveys on bank regulation that were conducted in 1999, 2003, 2007 and 2011. Therefore, in order to not constraint our sample, we simply duplicate the missing years with the latest survey values. Ffor 2000–2002, use the survey for 1999; for 2004–2006, the survey for 2003; for 2008–2101, the survey for 2007, and for 2011, the survey for 2012.

change in macroprudential tools differ among banks depending on their balance sheet characteristics. In particular, banks that are small, weakly capitalised and with a higher share of wholesale funding react more strongly to changes in these tools. Third, macroprudential policies seem more effective in a tightening than in an easing phase.

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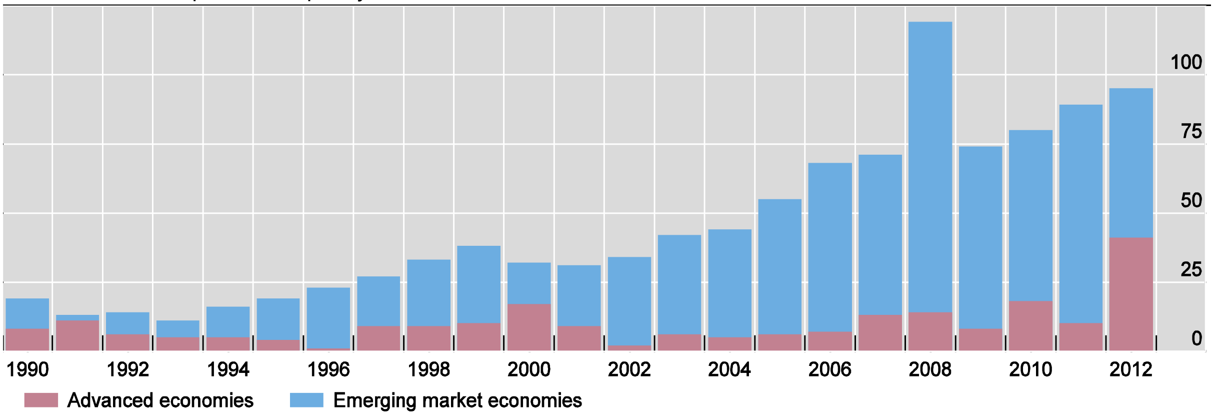
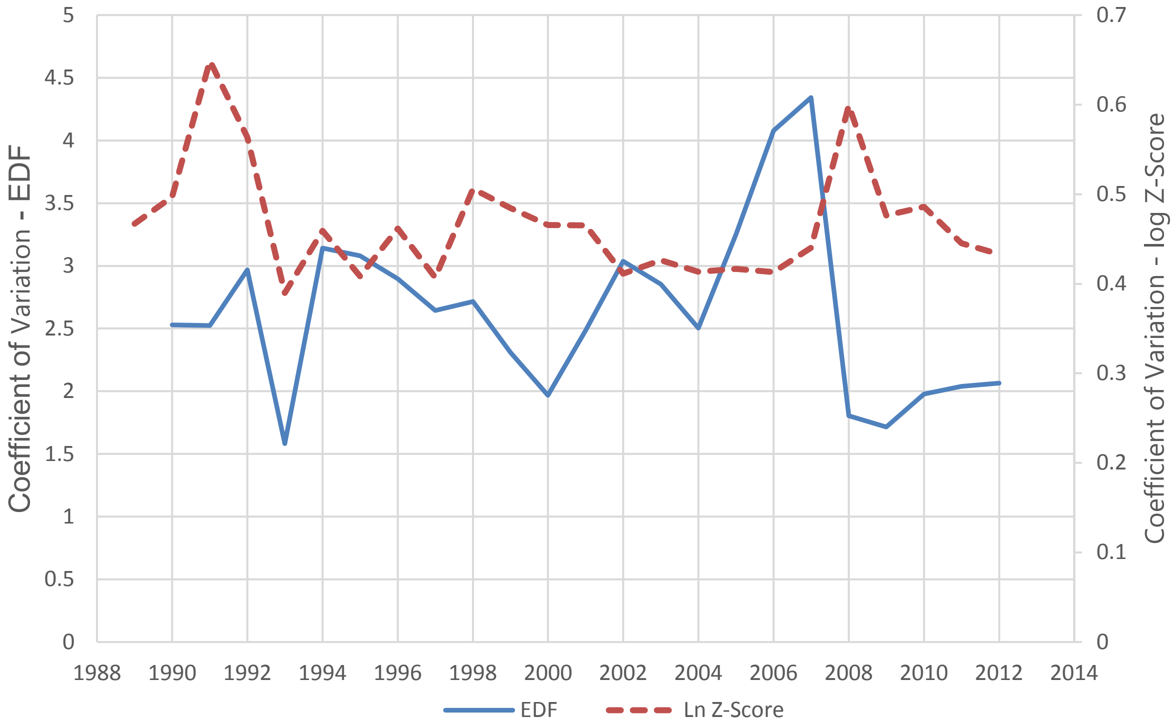
Figure 1: Macroprudential measures over time[1]

Number of macroprudential policy actions



[1] The sample covers 1,047 macroprudential policy actions adopted in 64 countries (29 advanced and 35 emerging market economies). The database has been constructed using information in Kuttner and Shim (2016) and Lim et al (2013).
Sources: IMF; BIS.

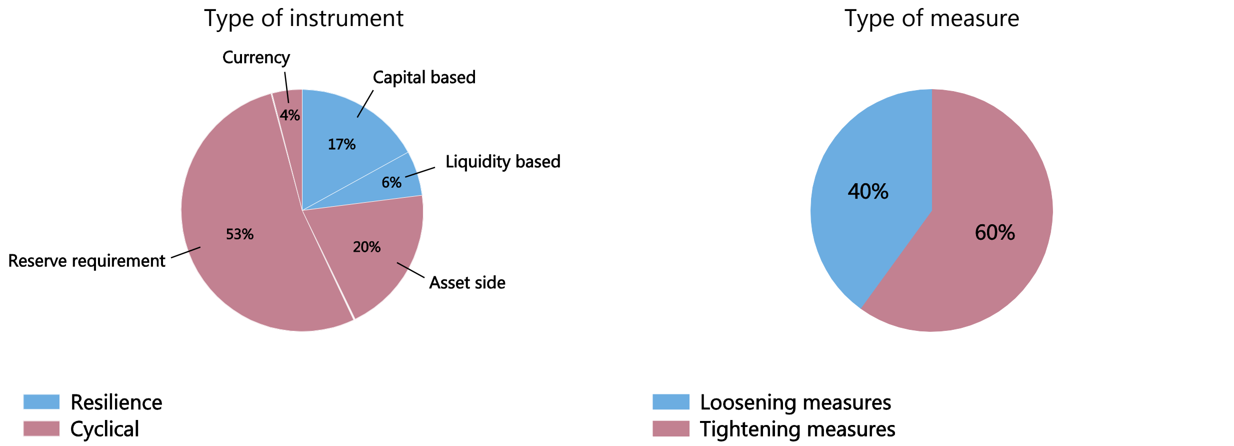
Figure 2: Cross-sectional dispersion of bank risk measures



Source: Authors' calculations.
Note: The coefficient of variation is given by the ratio of the standard error to the mean. The series show the coefficient of variation of banks' expected default frequency (left hand scale) and the Z-score (right hand scale) in each year.

Figure 3. Use of macroprudential instruments. Different kinds of policies

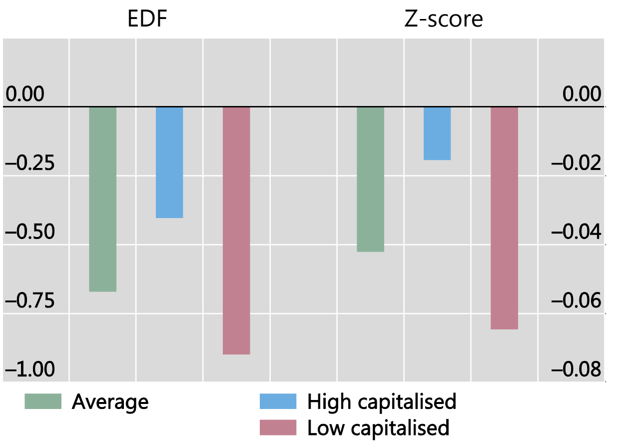
In percent



Note: Resilience macroprudential tools include: a) capital based instruments (countercyclical capital requirements, leverage restrictions, general or dynamic provisioning) and b) the establishment of liquidity requirements. Cyclical macroprudential tools consider: c) asset side instruments (credit growth limits, maximum debt service-to-income ratio, limits to banks' exposures to the housing sector as maximum loan to value ratio); d) changes in reserve requirements; e) currency instruments (variations in limits on foreign currency exchange mismatches and net open positions).

Source: IMF, BIS, authors' calculations.

Figure 4. Effect of a macroprudential tool tightening: well vs low capitalized banks

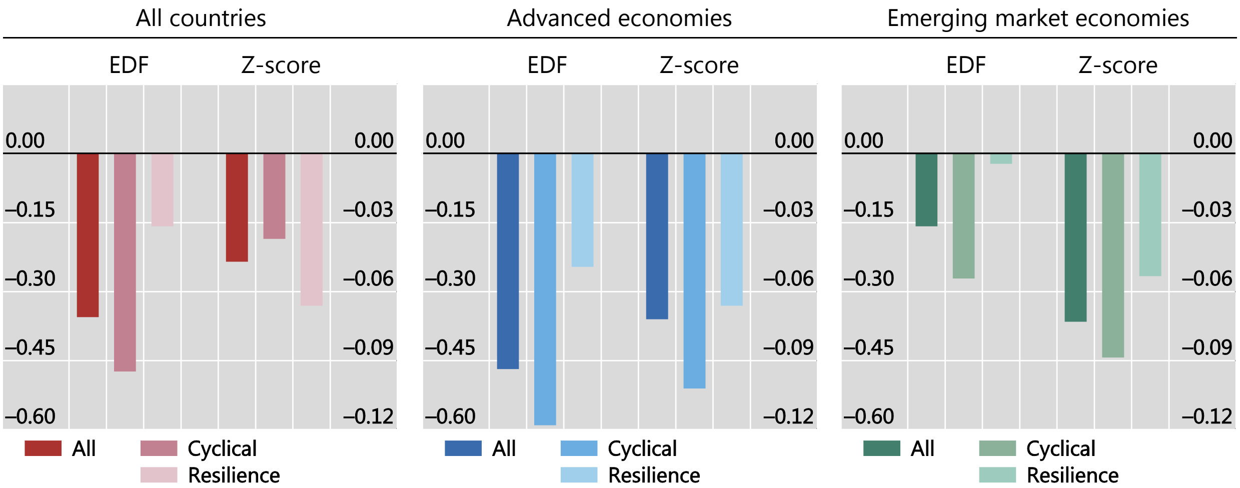


Note: The graph reports the effect on bank risk of a tightening in macroprudential tool. The left part indicates the effects on banks' expected default frequency (left-hand axis), the right part the effects on the Z-score (right-hand axis).

Source: Authors' calculations

Figure 5. Average impact of a macroprudential tightening on bank risk: Advanced vs emerging market economies

Expected default frequency (left hand side) and Z-score (right hand side)



Note: The Expected default frequency (EDF) represents the probability that a bank will default within one year. The *EDF* is a well-known, forward-looking indicator of risk, computed by Moody's KMV, which builds on Merton's model to price corporate bond debt (Merton, 1974). The *EDF* value, expressed as a percentage, is calculated by combining banks' financial statements with stock market information and Moody's proprietary default database. The Z-score is an alternative measure for risk and it can be summarized as $Z=(k+ROA)/\sigma_{ROA}$, where k is equity capital as percent of assets, ROA is average after-tax return as percent on assets, and σ_{ROA} is standard deviation of the after-tax return on assets, as a proxy for return volatility. The Z-score measures the number of standard deviations a return realization has to fall in order to deplete equity, under the assumption of normality of banks' returns. A higher Z-score corresponds to a lower upper bound of insolvency risk, a higher z-score therefore implies a lower probability of insolvency risk. To compare the signs of the coefficients in the regressions, we have therefore multiplied the *Z*-score by -1.
Source: Authors' calculations.

Table 1: Summary statistics of the variables used in the regressions (1990-2012)[1]

Variables	Number of observations	Mean	Median	Std. Dev	Min	Max	1st quartile	3rd quartile	Sources
Δ EDF	20,870	0.116	-0.003	2.094	-32.275	29.65	-0.111	0.157	Moody's KMV
Z-score	20,870	-2.685	-2.847	-1.256	-5.298	-4.605	-3.467	-2.078	Authors' calc.
Δ EDF_NFS	20,870	-0.069	-0.150	1.546	-6.448	8.236	-1.022	0.771	Moody's KMV
DIFF	20,870	-0.012	-0.009	0.025	-0.220	0.235	-0.023	0.001	IMF/WB/OECD
ΔGDP	20,870	2.760	2.720	2.967	-13.130	15.060	1.450	4.350	IMF/WB/OECD
DEP	20,870	0.000	0.067	1.180	-0.802	0.966	-0.076	0.136	BankScope
SIZE	20,870	0.000	-0.137	2.192	-16.031	7.932	-1.443	1.365	BankScope
CAP	20,870	0.000	-0.048	0.176	-0.141	0.879	-0.075	-0.015	BankScope
LIQ	20,870	0.000	-0.053	0.205	-0.267	0.783	-0.150	0.083	BankScope
MP index cum	20,870	0.100	0	0.589	-3	3	0	0	See Annex B
MP cyclical	20,870	0.001	0	0.440	-1	1	0	0	See Annex B
MP resilience	20,870	0.037	0	0.298	-1	1	0	0	See Annex B
MP_capital_easing	20,870	0.018	0	0.132	0	1	0	0	See Annex B
MP_liquidity_easing	20,870	0.011	0	0.106	0	1	0	0	See Annex B
MP_assets_easing	20,870	0.025	0	0.155	0	1	0	0	See Annex B
MP_currency_easing	20,870	0.005	0	0.069	0	1	0	0	See Annex B
MP_reserve_easing	20,870	0.071	0	0.257	0	1	0	0	See Annex B
MP_capital_tightening	20,870	0.066	0	0.248	0	1	0	0	See Annex B
MP_liquidity_tightening	20,870	0.012	0	0.109	0	1	0	0	See Annex B
MP_assets_tightening	20,870	0.08	0	0.271	0	1	0	0	See Annex B
MP_currency_tightening	20,870	0.012	0	0.110	0	1	0	0	See Annex B
MP_reserve_tightening	20,870	0.060	0	0.238	0	1	0	0	See Annex B
Regulatory strength	16,615	30.39	31	5.718	11	45	28	34	Barth et al (2013)
Banking crisis	20,870	0.040	0	0.195	0	1	0	0	Valencia and Laeven (2012)

Note: (1) Bank specific indicators are in mean deviation form.

where:
ΔEDF=change in the *EDF* at the bank level (1 year ahead)
Z-score = indicator of the probability of default which is computed on the base of balance sheet variables
ΔEDF_NFS = *EDF* change for the non-financial sector at the country level (1 year ahead)
DIFF = real money market interest rate minus natural rate
ΔGDP = changes in nominal *GDP*
DEP = deposit-to-total liability ratio *100
SIZE = log of total assets (USD millions)
CAP = capital-to-total asset ratio *100
*LIQ= cash and securities-to- total asset ratio*100*
MP index = aggregate macroprudential index
MP cyclical=index for macroprudential policies that aim at dampening cycle
MP resilience= index for macroprudential policies that aim at increasing system resilience MP_capital = capital based macroprudential tool
MP_liquidity = liquidity based macroprudential tool
MP_asset = asset side based macroprudential tool
MP_currency = currency requirement macroprudential tool
MP_reserve = reserve based macroprudential tool (reserve requirement)
Regulatory strength = index for overall banking regulation quality Bank crisis = dummy equal to 1 if the country where the bank is headquartered is in a banking crisis

Table 2: Balance sheet characteristics and bank risk profile [1]

	Lending	Size	Liquidity	Capitalization	Deposits	Cost to income ratio	ROA	ROA variability [2]	EDF / Z-Score
	(annual growth rate)	(USD mill.)	(% total assets)	(% total assets)	(% total assets)	(%)	(%)	(coefficient of variation)	(%)
Panel A: Distribution by bank risk (one-year ahead EDF)									
A1: Full Sample									
High-risk banks	5.085	15.551	15.523	13.460	70.351	73.425	0.312	83.506	7.356
Low-risk banks	14.268	16.251	17.923	16.995	67.256	58.835	2.588	41.575	0.070
A2: Advanced Economies									
High-risk banks	1.519	15.863	12.800	11.717	70.952	74.489	-0.086	76.408	8.318
Low-risk banks	13.820	16.279	17.510	15.616	67.210	59.631	2.330	41.144	0.060
A3: Emerging Economies									
High-risk banks	11.525	14.990	20.425	16.602	69.253	71.523	1.030	96.057	5.621
Low-risk banks	17.491	16.053	20.758	26.476	67.606	53.114	4.365	44.614	0.138
Panel A: Distribution by bank risk (Z-Score)									
A1: Full Sample									
High-risk banks	6.733	15.965	18.597	9.316	73.891	84.518	-0.138	84.627	0.227
Low-risk banks	9.310	15.749	11.167	12.339	74.793	58.546	1.045	15.440	4.390
A2: Advanced Economies									
High-risk banks	4.226	16.173	18.452	8.404	73.176	83.946	0.071	77.466	0.192
Low-risk banks	8.717	15.703	9.411	11.510	74.933	59.678	0.978	14.071	4.396
A3: Emerging Economies									
High-risk banks	12.847	15.455	18.952	11.542	75.651	85.906	-0.646	102.450	0.311
Low-risk banks	12.680	16.003	20.961	16.963	73.992	51.789	1.422	25.356	4.354

Note: (1) A low-risk bank has an average ratio of the *EDF (Z-score)* in the first decile of the distribution by bank risk; a high-risk bank an average EDF (Z-score) in the last decile.
(2) Coefficient of variation of the Return on Assets (*ROA*) is calculated for the 4 quarters ahead.

Table 3: Use of macroprudential instruments

Type of instrument	Total measures	Frequency of use (percent)	Tightening measures	Loosening measures
	(I)	(II)	(III)	(IV)
a. Capital based instruments	178	17.0	148	30
Capital requirement/Risk weights (RW)	127	12.1	108	19
Provisioning requirement (Prov)	51	4.9	40	11
b. Liquidity based instruments				
Liquidity requirements (Liq)	64	6.1	26	38
c. Asset side instruments	207	19.8	146	61
Credit growth limits (Credit)	51	4.9	31	20
Maximum debt-service-to-income ratio and other lending criteria (DSTI)	36	3.4	31	5
Limits on banks' exposure to the housing sector	11	1.1	7	4
Maximum loan-to-value ratio and loan prohibition (LTV)	109	10.4	77	32
d. Reserve requirement (RR)	558	53.3	278	280
e. Currency instruments	40	3.8	29	11
Net open position (NOP)	26	2.5	17	9
Foreign currency lending limits (FCL)	14	1.3	12	2
Total	*1,047*	*100*	*627*	*420*

Notes: The table shows the number of policy actions taken by the countries in the sample. Frequency of use in column (II) indicates the share of each policy action among the total in column (I).

Table 4: Baseline regression with aggregate macroprudential index

	Dependent variable: Annual change of the expected default frequency over a 1 year horizon (I)			(II)			Dependent variable: Annual change of the Z-score (III)			(IV)		
	Coeff		Std err	Coeff		Std err	Coeff		Std err	Coeff		Std err
Dependent variable$_{t-1}$	0.221	***	0.003	0.216	***	0.006	0.894	***	0.020	0.931	***	0.125
ΔEDF_NFS$_t$	0.411	***	0.067	0.395	***	0.060	0.019	***	0.005	0.018	***	0.005
DIFF$_t$	-0.012	**	0.006	-0.020	**	0.009	-0.01	**	0.005	-0.003	**	0.001
ΔGDP$_t$	-0.839		0.703	-0.533		0.671	-0.665	***	0.065	-0.423	***	0.113
SIZE$_{t-1}$	-0.01	***	0.003	-0.071	**	0.036	-0.021	***	0.003	-0.014	*	0.008
LIQ$_{t-1}$	-0.118	***	0.015	-0.090	*	0.051	-0.043	*	0.024	-0.075	**	0.036
CAP$_{t-1}$	-0.158	***	0.027	-1.027	**	0.468	-0.86	***	0.048	-0.517	**	0.244
DEP$_{t-1}$	-0.063	**	0.031	-0.627	***	0.216	-0.973	***	0.030	-0.678	***	0.240
MP_index$_t$	-0.655	***	0.066	-0.670	***	0.237	-0.007	**	0.003	-0.012	*	0.007
*MP_index$_t$*CAP$_{t-1}$*				3.189	***	0.357				0.317	***	0.032
*MP_index$_t$*SIZE$_{t-1}$*				0.491	***	0.057				0.007	*	0.004
*MP_index$_t$*LIQ$_{t-1}$*				0.201	*	0.116				-0.038		0.074
*MP_index$_t$*DEP$_{t-1}$*				0.194	*	0.117				0.247	***	0.030
Sample period	1990-2012			1990-2012			1990-2012			1990-2012		
Observations	20,870			20,870			20,870			20,870		
Serial correlation test[1]	0.110			0.140			0.066			0.127		
Hansen test[2]	0.560			0.640			0.730			0.760		

Notes: The database is composed of 3,177 banks headquartered in 61 countries. Robust standard errors (clustered at the bank-year level) are reported. The symbols *, **, and *** represent significance levels of 10%, 5%, and 1% respectively. The coefficient for the banking crisis dummy is not reported. [1] Reports p-values for the null hypothesis that the errors in the first difference regression exhibit no second order serial correlation. [2] Reports p-values for the null hypothesis that the instruments used are not correlated with the residuals.

Table 5: Cyclical vs Resilience macroprudential tools

	Dependent variable: Annual change of the expected default frequency over a 1 year horizon (I)			Dependent variable: Annual change of the Z-score (II)		
	Coeff		Std err	Coeff		Std err
Dependent variable$_{t-1}$	0.089	**	0.043	0.890	***	0.067
ΔEDF_NFS$_t$	0.614	***	0.090	0.032	***	0.005
DIFF$_t$	-0.041	**	0.019	-0.018	***	0.004
ΔGDP$_t$	-1.517		2.442	-0.768	***	0.261
SIZE$_{t-1}$	-0.053	*	0.027	-0.012	**	0.005
LIQ$_{t-1}$	-0.278	***	0.015	-0.158	***	0.060
CAP$_{t-1}$	-1.711	***	0.507	-0.425	***	0.112
DEP$_{t-1}$	-1.299	***	0.192	-0.547	***	0.100
MP_Cyclical index$_t$	-0.473	**	0.194	-0.037	*	0.020
MP_Resilience_index$_t$	-0.158	***	0.042	-0.066	***	0.001
*MP_Cyclical index$_t$ * CAP$_{t-1}$*	1.510	***	0.434	0.568	***	0.145
*MP_Cyclical index$_t$ * SIZE$_{t-1}$*	0.125	*	0.067	0.009	*	0.005
*MP_Cyclical index$_t$ * LIQ$_{t-1}$*	0.551	***	0.010	0.162	***	0.040
*MP_Cyclical index$_t$ * DEP$_{t-1}$*	0.545	**	0.237	0.117	*	0.069
*MP_ Resilience index$_t$ * CAP$_{t-1}$*	2.056	**	0.913	0.621	***	0.183
*MP_ Resilience index$_t$ * SIZE$_{t-1}$*	0.088	**	0.035	0.031	***	0.006
*MP_ Resilience index$_t$ * LIQ$_{t-1}$*	0.304	*	0.158	0.104	*	0.058
*MP_ Resilience index$_t$ * DEP$_{t-1}$*	1.501	**	0.737	0.101	***	0.020
Sample period	1990-2012			1990-2012		
Observations	20,870			20,870		
Serial correlation test[1]	0.077			0.275		
Hansen test[2]	0.358			0.180		

Notes: The database is composed of 3,177 banks headquartered in 61 countries. Robust standard errors (clustered at the bank-year level) are reported. The symbols *, **, and *** represent significance levels of 10%, 5%, and 1% respectively. The coefficient for the banking crisis dummy is not reported. [1]Reports p-values for the null hypothesis that the errors in the first difference regression exhibit no second order serial correlation. [2] Reports p-values for the null hypothesis that the instruments used are not correlated with the residuals.

Table 6: Bank-specific characteristics: Impact on EDF

Dependent variable: Annual change of the expected default frequency over a 1 year horizon	Baseline model (I)		Interactions with: bank size (II)		Interactions with: liquidity ratio (III)		Interactions with: leverage ratio (IV)		Interactions with: deposit ratio (V)	
	Coeff	Std err	Coeff	Std err	Coeff	Std err	Coeff	Std err	Coeff	Std err
Dependent variable$_{t-1}$	0.265***	0.027	0.235***	0.010	0.207***	0.012	0.234***	0.050	0.248***	0.001
ΔEDF_NFS$_t$	0.412***	0.028	0.216***	0.027	0.247***	0.026	0.236***	0.035	0.259***	0.048
DIFFt	-0.044***	0.004	-0.027**	0.012	-0.022*	0.012	-0.067***	0.012	-0.062***	0.007
ΔGDP$_t$	-0.060	1.503	-2.607**	1.140	-2.552**	1.190	-3.156***	0.396	-1.936**	0.820
SIZE$_{t-1}$	-0.020***	0.003	-0.020	0.025						
LIQ$_{t-1}$	-0.272***	0.022			-0.840*	0.505				
CAP$_{t-1}$	-0.704***	0.273					-0.258***	0.071		
DEP$_{t-1}$	-0.458***	0.054							-1.022***	0.182
MP_capital_easing$_t$	0.187***	0.024	0.105	0.261	0.331**	0.162	0.313***	0.106	0.473***	0.126
MP_liquidity_easing$_t$	0.153	0.168	0.552	0.339	0.346	0.246	0.046	0.098	0.004	0.003
MP_assets_easing$_t$	0.658***	0.297	0.657***	0.207	0.289**	0.144	0.437***	0.038	3.073***	0.351
MP_currency_easing$_t$	0.431***	0.056	1.033***	0.440	1.580***	0.358	1.970***	0.323	2.408***	0.529
MP_reserve_easing$_t$	0.898**	0.362	1.713***	0.422	1.372***	0.256	1.185***	0.289	1.683***	0.163
MP_capital_tightening$_t$	-0.475	0.302	-1.023*	0.531	-0.200	0.306	-0.553***	0.213	-0.689***	0.265
MP_liquidity_tightening$_t$	-0.213	0.300	-0.134	0.264	-0.043	0.200	-0.140	0.106	-0.034	0.192
MP_assets_tightening$_t$	-0.149***	0.013	-0.634***	0.194	-0.277	0.124	-0.275***	0.051	-0.113	0.246
MP_currency_tightening$_t$	-0.592***	0.140	-0.817***	0.266	-0.785***	0.216	-0.835***	0.079	-1.462***	0.441
MP_reserve_tightening$_t$	-1.487***	0.379	-1.828***	0.454	-1.143***	0.286	-1.955***	0.275	-1.806***	0.102
*MP_capital_easing$_t$*X$_{t-1}$*			-0.034	0.098	0.406	1.162	-1.941	1.882	-0.067	0.348
*MP_liquidity_easing$_t$*X$_{t-1}$*			0.146	0.158	-1.448	1.676	-0.430*	0.241	-0.632	0.656
*MP_assets_easing$_t$*X$_{t-1}$*			-0.155**	0.071	2.936	7.861	-0.601***	0.100	-6.927	4.596
*MP_currency_easing$_t$*X$_{t-1}$*			-0.881***	0.285	-0.607	1.863	-2.131***	0.365	-2.609	2.282
*MP_reserve_easing$_t$*X$_{t-1}$*			-0.499***	0.107	-0.331	0.934	-0.257	0.721	-0.270	0.280
*MP_capital_tightening$_t$*X$_{t-1}$*			0.258*	0.132	-0.143	0.868	0.378***	0.130	0.285	0.872
*MP_liquidity_tightening$_t$*X$_{t-1}$*			0.076	0.127	0.112	1.365	-0.648	0.940	1.062***	0.198
*MP_assets_tightening$_t$*X$_{t-1}$*			0.062	0.048	-0.760	0.915	0.553***	0.192	0.583	0.498
*MP_currency_tightening$_t$*X$_{t-1}$*			0.164*	0.098	-1.132	2.333	0.665***	0.244	4.978***	1.867
*MP_reserve_tightening$_t$*X$_{t-1}$*			0.426***	0.126	1.854*	1.034	1.662***	0.254	1.646***	0.350
Sample period	1990-2012		1990-2012		1990-2012		1990-2012		1990-2012	
Observations	20,870		20,870		20,870		20,870		20,870	
Serial correlation test[1]	0.120		0.408		0.342		0.534		0.304	
Hansen test[2]	0.709		0.690		0.780		0.423		0.760	

Notes: The database is composed of 3,177 banks headquartered in 61 countries. Robust standard errors (clustered at the bank-year level) are reported. The symbols *, **, and *** represent significance levels of 10%, 5%, and 1% respectively. The coefficient for the banking crisis dummy is not reported. [1] Reports p-values for the null hypothesis that the errors in the first difference regression exhibit no second order serial correlation. [2] Reports p-values for the null hypothesis that the instruments used are not correlated with the residuals.

Table 7: Bank-specific characteristics: Impact on Z-score

Dependent variable: Annual change of the Z-score	Baseline model (I)		Interactions with: bank size (II)		Interactions with: liquidity ratio (III)		Interactions with: leverage ratio (IV)		Interactions with: deposit ratio (V)	
	Coeff	Std err	Coeff	Std err	Coeff	Std err	Coeff	Std err	Coeff	Std err
Dependent variable$_{t-1}$	0.612***	0.009	0.655***	0.007	0.617***	0.030	0.626***	0.001	0.702***	0.039
ΔEDF_NFS$_t$	0.035***	0.004	0.020***	0.002	0.061***	0.007	0.032***	0.002	0.036***	0.008
DIFFt	-0.022***	0.003	-0.018***	0.001	-0.018***	0.004	-0.022***	0.005	-0.010***	0.002
ΔGDP$_t$	-2.014***	0.196	-1.479***	0.103	-1.614***	0.372	-1.258***	0.234	-1.046***	0.108
SIZE$_{t-1}$	-0.023**	0.011	-0.018***	0.001						
LIQ$_{t-1}$	-0.059	0.082			0.189	0.153				
CAP$_{t-1}$	-0.684***	0.203					-0.520***	0.164		
DEP$_{t-1}$	-0.466***	0.090							-0.379***	0.027
MP_capital_easing$_t$	0.037	0.041	0.225***	0.007	0.072*	0.042	-0.011	0.185	0.064***	0.013
MP_liquidity_easing$_t$	0.088	0.058	0.055***	0.005	-0.031	0.118	-0.034	0.029	-0.016	0.042
MP_assets_easing$_t$	0.156***	0.059	0.013	0.032	-0.022	0.036	0.006	0.038	0.039*	0.022
MP_currency_easing$_t$	0.392***	0.088	0.065	0.101	0.347***	0.077	0.166**	0.071	0.401***	0.039
MP_reserve_easing$_t$	0.087**	0.044	0.313***	0.013	-0.045	0.043	0.015	0.026	0.014	0.031
MP_capital_tightening$_t$	-0.040	0.040	-0.004	0.039	-0.026	0.030	0.018	0.013	-0.016	0.018
MP_liquidity_tightening$_t$	-0.188***	0.054	-0.218***	0.028	-0.369***	0.057	-0.107***	0.023	-0.167***	0.015
MP_assets_tightening$_t$	-0.154**	0.025	-0.014	0.009	-0.017	0.035	-0.040	0.058	-0.021**	0.009
MP_currency_tightening$_t$	-0.279***	0.053	-0.120***	0.025	-0.181***	0.044	-0.078***	0.030	-0.460***	0.014
MP_reserve_tightening$_t$	-0.074**	0.033	-0.163***	0.012	-0.045*	0.028	-0.090***	0.007	-0.053***	0.019
MP_capital_easing$_t$***X*$_{t-1}$			-0.103***	0.028	0.668	0.413	-1.123	1.703	-0.546***	0.037
MP_liquidity_easing$_t$***X*$_{t-1}$			-0.059***	0.005	-0.147	0.675	0.056	0.160	-0.443***	0.033
MP_assets_easing$_t$***X*$_{t-1}$			-0.002	0.012	-0.440*	0.249	-0.748	0.584	-1.244***	0.114
MP_currency_easing$_t$***X*$_{t-1}$			-0.062***	0.012	-0.397	0.481	-1.178***	0.236	0.545	1.431
MP_reserve_easing$_t$***X*$_{t-1}$			-0.080***	0.004	-0.494*	0.272	0.245	0.159	0.547	0.568
MP_capital_tightening$_t$***X*$_{t-1}$			0.000	0.012	1.351***	0.384	0.869***	0.108	0.444***	0.099
MP_liquidity_tightening$_t$***X*$_{t-1}$			0.045***	0.001	0.315	0.369	0.306***	0.097	-0.086	0.073
MP_assets_tightening$_t$***X*$_{t-1}$			-0.016*	0.009	-0.512	0.348	0.307***	0.070	-0.087	0.096
MP_currency_tightening$_t$***X*$_{t-1}$			-0.007	0.027	1.126***	0.347	1.718***	0.430	0.390***	0.104
MP_reserve_tightening$_t$***X*$_{t-1}$			0.040***	0.006	0.682**	0.332	1.567***	0.117	1.131***	0.044
Sample period	1990-2012		1990-2012		1990-2012		1990-2012		1990-2012	
Observations	20,870		20,870		20,870		20,870		20,870	
Serial correlation test[1]	0.242		0.104		0.270		0.119		0.101	
Hansen test[2]	0.699		0.690		0.590		0.760		0.600	

Notes: Robust standard errors (clustered at the bank-year level) are reported. The symbols *, **, and *** represent significance levels of 10%, 5%, and 1% respectively. The coefficient for the banking crisis dummy is not reported. [1] Reports p-values for the null hypothesis that the errors in the first difference regression exhibit no second order serial correlation. [2] Reports p-values for the null hypothesis that the instruments used are not correlated with the residuals.

Annex A: Descriptive statistics by country (mean values: 1990-2012)

Country	Nominal *GDP*	Money market rate	Bank size, total assets	Loan growth	Capital	Liquidity	*Deposits*	*EDF* (banks)	Z-score (1)	EDF non financial firms (2)	Banking crisis	Number of banks (3)	Weight inside sample (4)
	(Annual growth rate)	(Annual interest rate)	(log(USD millions))	(Annual growth rate)	(% of total assets)	(% of total assets)	(% of total assets)	(1 year ahead)	(%)	(Average quarterly changes)	(number of crisis)	(Final dataset)	(%)
AE	2.70	5.05	15.72	13.10	21.40	18.80	67.20	0.84	2.95	2.22	0.00	19	0.60
AR	4.40	11.25	15.47	8.60	14.00	31.80	71.40	1.84	1.85	5.28	0.08	8	0.25
AT	*2.00*	*2.43*	*15.91*	*5.90*	*13.40*	*19.40*	*62.20*	*0.90*	*3.12*	*2.50*	*0.09*	*31*	*0.98*
AU	*3.20*	*5.19*	*16.54*	*12.00*	*8.60*	*8.90*	*73.10*	*0.80*	*3.38*	*3.86*	*0.00*	*27*	*0.85*
BE	*1.70*	*2.77*	*17.65*	*5.30*	*14.70*	*17.90*	*68.70*	*1.09*	*2.30*	*2.35*	*0.05*	*21*	*0.66*
BH	5.20	2.51	15.22	3.10	19.30	21.50	61.00	1.86	2.51	0.20	0.00	15	0.47
BR	3.30	22.88	15.84	17.20	14.70	25.00	64.00	2.58	2.54	8.27	0.02	34	1.07
CA	*2.00*	*2.93*	*16.81*	*11.40*	*12.10*	*14.80*	*70.90*	*0.86*	*3.18*	*5.60*	*0.00*	*21*	*0.66*
CH	*1.80*	*1.65*	*15.07*	*7.60*	*28.60*	*26.90*	*58.20*	*0.91*	*2.78*	*1.54*	*0.06*	*49*	*1.54*
CL	4.50	5.02	15.87	16.10	10.50	15.20	71.90	0.37	3.26	2.56	0.00	13	0.41
CN	10.20	2.87	18.92	23.00	7.80	24.80	87.20	0.68	3.03	1.55	0.00	26	0.82
CO	4.30	9.04	15.20	17.00	18.40	17.80	72.30	1.31	3.04	2.46	0.02	13	0.41
CZ	2.50	4.40	15.97	10.10	8.20	17.80	82.50	0.51	2.44	3.51	0.00	10	0.31
DE	*1.50*	*3.00*	*15.97*	*4.70*	*13.60*	*23.00*	*56.60*	*2.39*	*2.53*	*3.71*	*0.07*	*88*	*2.77*
DK	*1.20*	*2.85*	*13.85*	*9.20*	*11.90*	*18.60*	*77.40*	*1.05*	*2.47*	*2.64*	*0.07*	*72*	*2.27*
EG	4.60	6.94	14.82	9.20	13.50	26.70	81.60	1.78	2.28	1.48	0.00	15	0.47
ES	*2.10*	*3.44*	*16.92*	*9.00*	*7.90*	*16.70*	*76.90*	*0.68*	*3.17*	*1.94*	*0.08*	*35*	*1.10*
FI	*2.50*	*3.43*	*15.24*	*8.30*	*28.40*	*14.20*	*62.40*	*0.39*	*2.53*	*1.69*	*0.00*	*22*	*0.69*
FR	*1.50*	*3.12*	*15.93*	*3.00*	*8.80*	*13.70*	*71.50*	*0.83*	*1.25*	*3.46*	*0.06*	*127*	*4.00*
GB	*2.50*	*4.22*	*15.95*	*6.80*	*28.30*	*28.90*	*53.30*	*0.97*	*2.52*	*3.39*	*0.07*	*132*	*4.15*

(continues on the next pages)

(Annex A - continued)

GR	*1.10*	*4.60*	*16.47*	*15.30*	*9.50*	*19.90*	*82.20*	*2.69*	*1.45*	*5.76*	*0.08*	*25*	*0.79*
HK	4.20	2.13	15.45	9.20	22.50	26.00	71.50	0.93	3.20	3.69	0.00	30	0.94
HU	1.70	7.35	15.51	15.00	8.20	16.70	61.70	1.71	2.37	4.60	0.08	9	0.28
ID	5.10	10.05	14.63	21.30	12.00	23.50	80.40	2.91	2.18	6.32	0.03	50	1.57
IE	*4.90*	*3.24*	*17.68*	*12.70*	*4.80*	*21.40*	*73.50*	*1.28*	*2.05*	*2.66*	*0.05*	*14*	*0.44*
IL	4.00	4.79	16.93	8.00	8.90	17.00	76.30	2.07	3.07	3.56	0.00	10	0.31
IN	7.40	10.17	16.05	18.90	11.30	16.00	75.50	1.85	2.93	6.11	0.00	61	1.92
IS	4.20	11.72	16.39	38.60	13.40	19.10	38.70	0.42	1.99	1.58	0.21	9	0.28
IT	*0.70*	*3.72*	*16.45*	*10.30*	*11.50*	*23.80*	*62.80*	*0.66*	*2.91*	*2.32*	*0.06*	*104*	*3.27*
JO	5.40	3.75	15.00	10.80	13.10	21.10	80.60	0.57	2.65	1.38	0.00	17	0.54
JP	*0.80*	*0.44*	*16.98*	*1.80*	*9.70*	*12.70*	*83.70*	*1.19*	*2.71*	*2.80*	*0.03*	*200*	*6.30*
KR	4.40	5.07	15.98	7.80	18.50	22.60	63.30	2.16	2.21	4.28	0.03	68	2.14
KW	3.80	2.53	14.69	4.60	34.80	20.40	57.40	1.63	1.73	1.61	0.00	18	0.57
LK	5.80	14.71	13.23	15.50	15.40	15.70	59.90	1.18	3.18	2.11	0.00	14	0.44
LU	*3.60*	*2.82*	*15.30*	*10.30*	*26.50*	*28.40*	*66.00*	*1.18*	*2.56*	*2.22*	*0.03*	*9*	*0.28*
MA	4.50	3.27	15.92	14.50	8.80	23.50	84.30	0.17	3.70	0.45	0.00	12	0.38
MX	2.70	11.73	15.58	17.60	19.80	29.60	64.90	1.71	1.94	3.34	0.01	12	0.38
MY	5.10	3.26	14.78	11.90	37.00	18.40	62.90	1.03	2.93	3.68	0.01	30	0.94
NL	*1.80*	*2.77*	*16.90*	*11.80*	*23.40*	*26.00*	*60.30*	*1.44*	*2.71*	*2.27*	*0.07*	*24*	*0.76*
NO	*1.80*	*4.74*	*14.85*	*9.00*	*9.80*	*7.70*	*62.80*	*1.57*	*3.12*	*3.96*	*0.00*	*52*	*1.64*
NZ	*2.80*	*5.35*	*16.04*	*8.10*	*5.50*	*7.40*	*81.50*	*4.71*	*3.01*	*3.12*	*0.00*	*5*	*0.16*
PA	5.50	4.81	12.61	17.70	9.30	17.50	80.60	1.27	3.81	0.65	0.00	1	0.03
PE	5.50	5.91	14.97	14.80	10.20	22.10	81.80	2.09	2.71	5.54	0.00	13	0.41
PH	4.70	7.19	14.50	9.70	16.30	27.10	75.40	1.51	3.34	6.01	0.02	32	1.01
PK	4.20	9.57	14.30	10.00	12.40	19.30	80.90	3.32	1.94	8.56	0.00	29	0.91

(Annex A - continued)

PL	3.90	5.86	15.68	15.10	10.90	16.30	80.60	1.10	2.77	3.99	0.00	33	1.04
PT	*1.10*	*3.00*	*16.20*	*8.00*	*12.20*	*23.60*	*70.50*	*1.20*	*2.69*	*4.77*	*0.07*	*20*	*0.63*
QA	14.70	4.90	16.04	22.80	17.40	20.00	76.20	0.49	3.45	0.40	0.00	5	0.16
RU	3.40	4.82	16.20	16.70	15.40	23.20	60.40	2.86	2.33	6.43	0.14	27	0.85
SA	6.30	1.24	17.02	12.90	13.30	14.30	81.80	0.86	2.77	0.40	0.00	8	0.25
SE	*2.40*	*3.36*	*16.76*	*8.50*	*13.10*	*25.10*	*60.30*	*2.12*	*2.24*	*3.50*	*0.07*	*21*	*0.66*
SG	5.80	1.83	15.55	9.50	32.90	20.40	63.00	0.31	3.48	3.25	0.00	29	0.91
SI	-0.30	1.69	15.66	2.70	7.00	9.80	78.90	4.20	1.18	4.81	0.22	2	0.06
SK	4.10	3.28	15.59	5.90	8.20	15.30	78.80	2.46	2.48	16.25	0.03	5	0.16
TH	4.20	3.78	14.56	10.10	24.50	14.60	69.20	2.05	1.80	4.02	0.03	51	1.61
TR	4.60	32.78	16.08	21.70	14.60	20.40	72.30	2.02	2.18	3.21	0.06	30	0.94
TW	4.00	2.98	15.70	5.90	20.60	19.40	63.50	1.17	2.62	2.60	0.00	67	2.11
US	*2.30*	*2.84*	*15.49*	*10.60*	*9.90*	*9.70*	*72.50*	*1.57*	*3.00*	*6.74*	*0.08*	*1,212*	*38.15*
VE	3.50	15.24	14.96	30.30	10.40	25.00	85.40	1.68	2.22	7.19	0.00	11	0.35
ZA	3.50	8.94	14.59	9.50	40.80	22.80	56.80	0.90	2.56	5.48	0.00	26	0.82
ZW	-10.10	123.07	11.67	38.90	19.30	41.80	64.60	1.66	0.82	0.48	0.00	4	0.13
Total	2.70	4.41	15.77	9.70	14.20	16.70	71.40	1.39	2.70	4.48	0.05	3,177	100.00

Sources: Bloomberg, OECD, Eurostat, Datastream, Moody's KMV, Creditedge and BIS. Advanced economies are indicated in italics. Notes: (1) The Z-score is an indicator of the probability of default which is computed on the base of balance sheet variables. The methodology is described in Altman et al. (1994). (2) EDF change for the non-financial sector in a country. The source is Moody’s KMV. (3) Banks analysed in this table refer to the final dataset after the filtering process and other corrections. (4) As a percentage of the number of observations.

Annex B: Additional details on the construction of the database on macroprudential tools

Our primary data sources for macroprudential measures are Shim et al (2013) and Lim et al (2011, 2013).

The first data base covers policy actions on housing markets for 60 economies worldwide from January 1990 (or earliest date available) to June 2012. It draws on a variety of sources including official documents from central banks' and regulatory authorities' annual reports, financial stability reports, monetary policy bulletins. Shim et al (2013) complement and cross-check official sources and documents with Borio and Shim (2007), survey by the Committee on the Global Financial System (CGFS) on macroprudential policy conducted in December 2009, Hilbers et al (2005), Crowe et al (2011), Lim et al (2011), and Tovar et al (2012). Thus, the database covers a wide range of countries and measures, as well as a long time span on macro-prudential measures. The policy actions in the database are categorized under general and targeted credit policy measures including minimum reserve requirements, liquidity requirements and limits on credit growth, maximum loan-to-value ratios, maximum debt-service-to-income ratios, risk weights on housing loans, provisioning requirements (general loan-loss provisioning ratios and specific provisioning ratios applied to housing loans) and exposure limits on banks to the housing sector. While the main aim of Shim et al (2013) is to document policy actions related to the housing market, they also include measure in the data set even if a central bank or another other authority changes policy decision for reasons other than the state of the housing market. Thus, their data set contains prudential measures taken from both microprudential and macroprudential perspectives.

The second study that we use to construct macro-prudential measures is Lim et al (2013) which is based on the 2010 IMF survey on Financial Stability and Macroprudential Policy. Lim et al (2013) update and extend the survey to assess if institutional arrangements can affect the timely use of macro-prudential policy instruments by evaluating policy response time under different institutional arrangements for a sample of 39 countries. Another study that also uses the IMF survey in 2010 is Lim et al (2011) that provides a comprehensive empirical study on the effectiveness of macroprudential instruments by using data from 49 countries over the period of 2000-2010. The IMF survey and both reference studies identify 10 instruments that have been most frequently applied to achieve macro-prudential objective that is "to limit the risk of widespread disruptions to the provision of financial services and thereby minimize the impact of such disruptions on the economy as a whole." (IMF, 2011, pp 7). These instruments are classified as credit-related (i.e., caps on the loan-to-value ratio, caps on the debt-to-income ratio, caps on foreign currency lending and ceilings on credit or credit growth); liquidity-related (i.e. limits on net open currency positions/currency mismatch, limits on maturity mismatch and reserve requirements), and capital-related (i.e. countercyclical/time-varying capital requirements, time-varying/dynamic provisioning, and restrictions on profit distribution) measures.

Using the two sources above we construct a database of macro-prudential measures for 64 countries from 1990 to 2012. The macro-prudential measures are classified under 10 categories including credit growth limits (Credit), liquidity requirements (Liq), maximum debt-service-to-income ratio and other lending criteria (DSTI), capital requirement/risk weights (RW), provisioning requirement (Prov), limits on banks' exposure to the housing sector (Expo), reserve requirement (RR), maximum loan-to-value ratio and loan prohibition (LTV), limits on net open position (NOP), and foreign currency lending limits (FCL). If a policy action is covered by both Shim et al (2013) and Lim et al (2013), then we compare and cross-checks both data bases, and include additional measures such as limits on net open positions and foreign currency lending as these instruments are not directly or indirectly aiming policy actions on housing markets. The set of instruments covered here would capture broad categories of systemic risk that could be linked to risk-taking channel such as risks arising from strong credit growth and credit-driven asset price inflation, excessive leverage and the consequent deleveraging, systemic liquidity risk, and risks related to large and volatile capital flows, including foreign currency lending.

Given the heterogeneity across policy instruments and actions, we follow Kuttner and Shim (2013) to create monthly variables that take on three discrete values: 1 for tightening actions, –1 for loosening actions and 0 for no change. Since the frequency of bank level and macroeconomic data used in our study is annual, then the monthly observations are summed to create yearly time series. Thus, both policy action's intensity and their directions would be captured by summing monthly data over each year which could take value of -1 or 1; -2 or 2; -3 or 3, and up to -12 or 12 or more. When macroprudential index is constructed for each instrument, and tightening and easing actions are aggregated over the year, then actions in opposite directions may cancel each other leaving with no net change. In final analysis, we investigate also the impact of easing and tightening separately using indicator variable 0 or 1 (no change or change in policy measure).

Based on our coding we observe 1,047 policy actions associated with ten different types of macroprudential tools (see Table 3). Among these policy measures reserve requirements are the most frequently used ones followed by loan-to-value ratio and capital requirements/risk weights. The reason for the frequent changes in reserve requirements is that this policy tools could be used for broad purposed, and could directly influence the liquidity conditions in the market. Additionally, in same cases in emerging economies, it also serves as capital flow management device by setting higher rates on foreign currency and external short term funding of the banking sector or longer maintenance period for certain types of liabilities.

Annex C: Robustness checks

Table C1: Baseline regression with aggregate macroprudential index (only advanced economies)

	Dependent variable: Annual change of the expected default frequency over a 1 year horizon						Dependent variable: Annual change of the Z-score					
	(I)			(II)			(III)			(IV)		
	Coeff		Std err	Coeff		Std err	Coeff		Std err	Coeff		Std err
Dependent variable$_{t-1}$	0.350	***	0.0184	0.343	***	0.0136	0.944	***	0.0519	0.976	***	0.0178
ΔEDF_NFS_t	0.264	***	0.0530	0.350	***	0.0772	0.029	***	0.0068	0.006	***	0.0020
$DIFF_t$	-0.099	**	0.0488	-0.022	***	0.0055	-0.024	**	0.0095	-0.010	**	0.0046
ΔGDP_t	-0.840		1.5823	-1.186		1.4491	-0.772	***	0.2571	-0.475	***	0.0402
$SIZE_{t-1}$	-0.015	**	0.0060	-0.027	***	0.0050	-0.014	**	0.0061	-0.027	***	0.0048
LIQ_{t-1}	-0.265	**	0.1071	-0.191	***	0.0349	-0.135	***	0.0337	-0.130	***	0.0077
CAP_{t-1}	-0.586	***	0.0211	-0.778	***	0.1834	-0.426	***	0.1455	-0.832	***	0.1898
DEP_{t-1}	-0.472	***	0.1722	-0.558	***	0.1869	-0.613	***	0.1007	-0.999	***	0.1797
MP_index_t	-0.469	**	0.1958	-0.672	*	0.3939	-0.072	**	0.0364	-0.169	***	0.0193
*MP_index_t*CAP_{t-1}*				1.629	*	0.8792				0.726	**	0.3232
*MP_index_t*$SIZE_{t-1}$*				0.189	***	0.0666				0.066	**	0.0273
*MP_index_t*LIQ_{t-1}*				0.430	**	0.1852				0.256	***	0.0329
*MP_index_t*DEP_{t-1}*				1.235		1.1886				0.476	***	0.1613
Sample period	1990-2012			1990-2012			1990-2012			1990-2012		
Observations	15,114			15,114			15,114			15,114		
Serial correlation test[1]	0.076			0.078			0.16			0.138		
Hansen test[2]	0.229			0.11			0.123			0.11		

Notes: The database is composed of 2,286 banks headquartered in advanced economies. Robust standard errors (clustered at the bank year level) are reported. The symbols *, **, and *** represent significance levels of 10%, 5%, and 1% respectively. The coefficient for the banking crisis dummy is not reported. [1] Reports p-values for the null hypothesis that the errors in the first difference regression exhibit no second order serial correlation. [2] Reports p-values for the null hypothesis that the instruments used are not correlated with the residuals.

Table C2: Cyclical vs Resilience macroprudential tools (only advanced economies)

	Dependent variable: Annual change of the expected default frequency over a 1 year horizon (I)			Dependent variable: Annual change of the Z-score (II)		
	Coeff		Std err	Coeff		Std err
Dependent variable$_{t-1}$	0.286	***	0.0147	0.948	***	0.1653
ΔEDF_NFS$_t$	0.430	**	0.1740	0.035	***	0.0095
DIFF$_t$	-0.090	***	0.0176	-0.035	***	0.0075
ΔGDP$_t$	-1.276		1.8909	-0.571	**	0.2319
SIZE$_{t-1}$	-0.023	**	0.0105	-0.010	***	0.0037
LIQ$_{t-1}$	-0.298	**	0.1423	-0.260	*	0.1458
CAP$_{t-1}$	-0.785	**	0.3883	-0.257	***	0.0096
DEP$_{t-1}$	-0.575	**	0.2649	-0.483	***	0.0925
MP_cyclical index$_t$	-0.596	***	0.0659	-0.102	***	0.0162
MP_resilience_index$_t$	-0.246	***	0.0344	-0.066	***	0.0229
*MP_Cyclical index$_t$ * CAP$_{t-1}$*	1.358	***	0.1562	0.128		0.0875
*MP_Cyclical index$_t$ * SIZE$_{t-1}$*	0.160	***	0.0287	0.076	***	0.0013
*MP_Cyclical index$_t$ * LIQ$_{t-1}$*	0.747		0.4618	0.151		0.1494
*MP_Cyclical index$_t$ * DEP$_{t-1}$*	0.542	**	0.2677	0.066	**	0.0290
*MP_ Resilience index$_t$ * CAP$_{t-1}$*	2.673	***	0.6203	0.212	**	0.0933
*MP_ Resilience index$_t$ * SIZE$_{t-1}$*	0.062	***	0.0180	0.044	***	0.0138
*MP_ Resilience index$_t$ * LIQ$_{t-1}$*	0.706	**	0.3490	1.561	**	0.6202
*MP_ Resilience index$_t$ * DEP$_{t-1}$*	1.689	**	0.7612	0.185	***	0.0521
Sample period	1990-2012			1990-2012		
Observations	15,114			15,114		
Serial correlation test[1]	0.089			0.129		
Hansen test[2]	0.558			0.278		

Notes: The database is composed of 2,286 banks headquartered in advanced economies. Robust standard errors (clustered at the bank year level) are reported. The symbols *, **, and *** represent significance levels of 10%, 5%, and 1% respectively. The coefficient for the banking crisis dummy is not reported. [1]Reports p-values for the null hypothesis that the errors in the first difference regression exhibit no second order serial correlation. [2] Reports p-values for the null hypothesis that the instruments used are not correlated with the residuals.

Table C3: Baseline regression with aggregate macroprudential index (only emerging market economies)

	Dependent variable: Annual change of the expected default frequency over a 1 year horizon (I)			(II)			Dependent variable: Annual change of the Z-score (III)			(IV)		
	Coeff		Std err	Coeff		Std err	Coeff		Std err	Coeff		Std err
Dependent variable$_{t-1}$	0.067	***	0.003	0.218	***	0.036	0.887	***	0.059	0.880	***	0.063
ΔEDF_NFS$_t$	0.895	***	0.026	0.702	***	0.254	0.038	**	0.015	0.032	***	0.007
DIFF$_t$	-0.064	***	0.019	-0.014	**	0.007	-0.001	***	0.000	-0.002	*	0.001
ΔGDP$_t$	-0.952	*	0.522	-1.201	*	0.729	-0.441	*	0.240	-0.313	**	0.151
SIZE$_{t-1}$	-0.060	***	0.017	-0.113	***	0.039	-0.012	***	0.004	-0.016	***	0.003
LIQ$_{t-1}$	-0.009		0.088	0.199		0.360	-0.236	***	0.059	-0.383	**	0.150
CAP$_{t-1}$	-1.849	**	0.921	-2.319	***	0.579	-0.733	**	0.287	-0.362	**	0.178
DEP$_{t-1}$	-1.784	**	0.774	-1.730	***	0.439	-0.868	***	0.254	-0.555	***	0.175
MP_index$_t$	-0.158	***	0.017	-0.883	***	0.051	-0.073	***	0.005	-0.024	**	0.012
*MP_index$_t$*CAP$_{t-1}$*				2.784	***	0.056				0.556	***	0.188
*MP_index$_t$*SIZE$_{t-1}$*				0.303	**	0.146				0.004	***	0.000
*MP_index$_t$*LIQ$_{t-1}$*				0.340		0.343				0.095	*	0.055
*MP_index$_t$*DEP$_{t-1}$*				0.679	***	0.022				0.509	***	0.128
Sample period	1990-2012			1990-2012			1990-2012			1990-2012		
Observations	5,756			5,756			5,756			5,756		
Serial correlation test[1]	0.089			0.156			0.359			0.348		
Hansen test[2]	0.706			0.169			0.177			0.248		

Notes: The database is composed of 891 banks headquartered in emerging market economies. Robust standard errors (clustered at the bank year level) are reported. The symbols *, **, and *** represent significance levels of 10%, 5%, and 1% respectively. The coefficient for the banking crisis dummy is not reported. [1] Reports p-values for the null hypothesis that the errors in the first difference regression exhibit no second order serial correlation. [2] Reports p-values for the null hypothesis that the instruments used are not correlated with the residuals.

Table C4: Cyclical vs Resilience macroprudential tools (only emerging market economies)

	Dependent variable: Annual change of the expected default frequency over a 1 year horizon (I)			Dependent variable: Annual change of the Z-score (II)		
	Coeff		Std err	Coeff		Std err
Dependent variable$_{t-1}$	0.0225	**	0.0106	0.8579	***	0.0401
ΔEDF_NFS$_t$	0.4014	***	0.0892	0.0572	***	0.0068
DIFF$_t$	-0.0050	**	0.0022	-0.0043	***	0.0015
ΔGDP$_t$	-1.3650	*	0.7523	-0.6346	***	0.0489
SIZE$_{t-1}$	-0.0684	**	0.0270	-0.0313	***	0.0022
LIQ$_{t-1}$	-0.2692	***	0.0404	-0.2651	***	0.0873
CAP$_{t-1}$	-0.1816	***	0.0620	-0.3468	***	0.0882
DEP$_{t-1}$	-0.0492		0.0881	-0.3023	**	0.1262
MP_cyclical index$_t$	-0.2715	***	0.0557	-0.0885	***	0.0142
MP_resilience_index$_t$	-0.0129	**	0.0052	-0.0532	***	0.0004
*MP_Cyclical index$_t$ *C AP$_{t-1}$*	4.5583	***	0.6487	0.5115	**	0.2416
*MP_Cyclical index$_t$ * SIZE$_{t-1}$*	0.4135	***	0.0753	0.0430	***	0.0137
*MP_Cyclical index$_t$ * LIQ$_{t-1}$*	0.0933		0.4506	0.0967		0.1879
*MP_Cyclical index$_t$ * DEP$_{t-1}$*	1.0434	***	0.1613	0.1406	***	0.0217
*MP_ Resilience index$_t$ * CAP$_{t-1}$*	1.5232	***	0.3118	0.5416	***	0.1774
*MP_ Resilience index$_t$ * SIZE$_{t-1}$*	0.0447	***	0.0035	0.0242	***	0.0009
*MP_ Resilience index$_t$ * LIQ$_{t-1}$*	0.9982	***	0.0235	0.0001		0.0093
*MP_ Resilience index$_t$ * DEP$_{t-1}$*	0.5627	***	0.0440	0.1936	***	0.0073
Sample period	1990-2012			1990-2012		
Observations	5,756			5,756		
Serial correlation test[1]	0.163			0.406		
Hansen test[2]	0.158			0.100		

Notes: The database is composed of 891 banks headquartered in emerging market economies. Robust standard errors (clustered at the bank year level) are reported. The symbols *, **, and *** represent significance levels of 10%, 5%, and 1% respectively. The coefficient for the banking crisis dummy is not reported. [1]Reports p-values for the null hypothesis that the errors in the first difference regression exhibit no second order serial correlation. [2] Reports p-values for the null hypothesis that the instruments used are not correlated with the residuals.

Table C5: Baseline regression with aggregate macroprudential index (only pre-crisis period)

	Dependent variable: Annual change of the expected default frequency over a 1 year horizon (I)			(II)			Dependent variable: Annual change of the Z-score (III)			(IV)		
	Coeff		Std err	Coeff		Std err	Coeff		Std err	Coeff		Std err
Dependent variable$_{t-1}$	0.097	**	0.039	0.104	***	0.018	0.921	***	0.015	0.946	***	0.018
ΔEDF_NFS_t	0.176	**	0.069	0.387	**	0.173	0.012	**	0.005	0.006	*	0.003
$DIFF_t$	-0.014	***	0.001	-0.014	**	0.006	-0.004	**	0.002	-0.007	***	0.002
ΔGDP_t	-1.997		1.546	-1.562		2.095	-0.941	**	0.411	-0.959	***	0.359
$SIZE_{t-1}$	-0.006		0.012	0.002		0.014	-0.020	**	0.010	-0.018	**	0.008
LIQ_{t-1}	-0.192	***	0.010	-0.154		0.197	-0.058	**	0.029	0.019		0.045
CAP_{t-1}	-0.770	**	0.388	-9.946	***	1.978	-0.793	***	0.073	-0.622	***	0.052
DEP_{t-1}	-0.777	*	0.433	-2.186	***	0.627	-0.972	**	0.396	-0.793	**	0.339
MP_index_t	-0.053	**	0.027	-0.066	**	0.029	-0.036	**	0.017	-0.097	**	0.039
$MP\_index_t*CAP_{t-1}$				1.887	***	0.591				0.234	***	0.052
$MP\_index_t*SIZE_{t-1}$				0.051	***	0.015				0.038	***	0.008
$MP\_index_t*LIQ_{t-1}$				0.213	*	0.119				0.190	**	0.087
$MP\_index_t*DEP_{t-1}$				2.045	***	0.757				0.037	*	0.020
Sample period	1990-2007			1990-2007			1990-2007			1990-2007		
Observations	13,460			13,460			13,460			13,460		
Serial correlation test[1]	0.061			0.056			0.064			0.104		
Hansen test[2]	0.155			0.17			0.147			0.429		

Notes: The database is composed of 3,177 banks headquartered in 61 countries. We include only observations for the pre-crisis period. Robust standard errors (clustered at the bank year level) are reported. The symbols *, **, and *** represent significance levels of 10%, 5%, and 1% respectively. The coefficient for the banking crisis dummy is not reported. [1] Reports p-values for the null hypothesis that the errors in the first difference regression exhibit no second order serial correlation. [2] Reports p-values for the null hypothesis that the instruments used are not correlated with the residuals.

Table C6: Cyclical vs Resilience macroprudential tools (only pre-crisis period)

	Dependent variable: Annual change of the expected default frequency over a 1 year horizon (I)			Dependent variable: Annual change of the Z-score (II)		
	Coeff		Std err	Coeff		Std err
Dependent variable$_{t-1}$	0.182	***	0.0117	0.894	***	0.0644
ΔEDF_NFS$_t$	0.138	**	0.0698	0.041	***	0.0136
DIFF$_t$	-0.007	*	0.0038	-0.021	***	0.0038
ΔGDP$_t$	-1.945		1.1855	-0.864	*	0.4827
SIZE$_{t-1}$	-0.013	**	0.0068	-0.011	*	0.0057
LIQ$_{t-1}$	-0.242	***	0.0070	-0.101		0.1319
CAP$_{t-1}$	-0.842	**	0.3602	-0.355	**	0.1588
DEP$_{t-1}$	-0.795	**	0.3959	-0.470		0.2918
MP_Cyclical index$_t$	-0.742	***	0.0786	-0.023	**	0.0096
MP_Resilience_index$_t$	-0.043	**	0.0175	-0.019	***	0.0026
*MP_Cyclical index$_t$ * CAP$_{t-1}$*	1.666	***	0.0281	0.579	***	0.0910
*MP_Cyclical index$_t$ * SIZE$_{t-1}$*	0.242	*	0.1288	0.010		0.0099
*MP_Cyclical index$_t$ * LIQ$_{t-1}$*	0.039		0.0358	0.148	**	0.0695
*MP_Cyclical index$_t$ * DEP$_{t-1}$*	0.321	***	0.0700	0.100		0.0657
*MP_ Resilience index$_t$ * CAP$_{t-1}$*	0.836	**	0.3958	0.587	**	0.2558
*MP_ Resilience index$_t$ * SIZE$_{t-1}$*	0.035	*	0.0198	0.020	***	0.0038
*MP_ Resilience index$_t$ * LIQ$_{t-1}$*	0.347	***	0.1077	0.161	***	0.0315
*MP_ Resilience index$_t$ * DEP$_{t-1}$*	0.961	***	0.3248	0.181	**	0.0858
Sample period	1990-2007			1990-2007		
Observations	13,460			13,460		
Serial correlation test[1]	0.069			0.053		
Hansen test[2]	0.758			0.114		

Notes: The database is composed of 3,177 banks headquartered in 61 countries. We include only observations for the pre-crisis period. Robust standard errors (clustered at the bank year level) are reported. The symbols *, **, and *** represent significance levels of 10%, 5%, and 1% respectively. The coefficient for the banking crisis dummy is not reported. [1]Reports p-values for the null hypothesis that the errors in the first difference regression exhibit no second order serial correlation. [2] Reports p-values for the null hypothesis that the instruments used are not correlated with the residuals.

Table C7: Baseline regression with aggregate macroprudential index (including time dummies)

	Dependent variable: Annual change of the expected default frequency over a 1 year horizon (I)			(II)			Dependent variable: Annual change of the Z-score (III)			(IV)		
	Coeff		Std err	Coeff		Std err	Coeff		Std err	Coeff		Std err
Dependent variable$_{t-1}$	0.258	***	0.034	0.167	***	0.048	0.880	***	0.077	0.900	***	0.190
ΔEDF_NFS$_t$	0.770	***	0.099	1.318	***	0.055	0.088	***	0.017	0.081	***	0.020
DIFF$_t$	-0.005	***	0.002	-0.035	**	0.014	-0.015	**	0.007	-0.015	***	0.004
ΔGDP$_t$	0.644		1.199	-1.200		1.103	-1.548	***	0.136	-1.248	**	0.558
SIZE$_{t-1}$	-0.022		0.014	-0.092	***	0.021	-0.028	***	0.004	-0.019		0.015
LIQ$_{t-1}$	-0.232	***	0.034	-0.599	***	0.120	-0.041	**	0.018	-0.070		0.059
CAP$_{t-1}$	-0.374	***	0.145	-1.534	***	0.192	-1.082	***	0.122	-0.579	**	0.226
DEP$_{t-1}$	-0.174	**	0.075	-1.123	***	0.243	-1.170	***	0.215	-0.753	**	0.312
MP_index$_t$	-0.346	**	0.161	-1.702	*	0.879	-0.023	**	0.010	-0.062	**	0.031
*MP_index$_t$*CAP$_{t-1}$*				14.992	**	6.133				0.129	*	0.067
*MP_index$_t$*SIZE$_{t-1}$*				0.404	**	0.171				0.006	**	0.003
*MP_index$_t$*LIQ$_{t-1}$*				3.375		2.803				0.152		0.095
*MP_index$_t$*DEP$_{t-1}$*				11.556	**	5.139				0.340	**	0.163
Time dummies	yes			yes			yes			yes		
Sample period	1990-2012			1990-2012			1990-2012			1990-2012		
Observations	20,870			20,870			20,870			20,870		
Serial correlation test[1]	0.092			0.096			0.084			0.126		
Hansen test[2]	0.716			0.720			0.054			0.178		

Notes: The database is composed of 3,177 banks headquartered in 61 countries. Robust standard errors (clustered at the bank year level) are reported. The symbols *, **, and *** represent significance levels of 10%, 5%, and 1% respectively. The coefficient for the banking crisis dummy is not reported. [1] Reports p-values for the null hypothesis that the errors in the first difference regression exhibit no second order serial correlation. [2] Reports p-values for the null hypothesis that the instruments used are not correlated with the residuals.

Table C8: Cyclical vs Resilience macroprudential tools (including time dummies)

	Dependent variable: Annual change of the expected default frequency over a 1 year horizon (I)			Dependent variable: Annual change of the Z-score (II)		
	Coeff		Std err	Coeff		Std err
Dependent variable$_{t-1}$	0.201	***	0.0215	0.903	***	0.2174
ΔEDF_NFS$_t$	0.540	***	0.1792	0.125	***	0.0414
DIFF$_t$	-0.029	***	0.0082	-0.025	**	0.0100
ΔGDP$_t$	-1.237		1.1132	-1.933	*	1.1591
SIZE$_{t-1}$	-0.064	*	0.0382	-0.017	**	0.0083
LIQ$_{t-1}$	-0.556	**	0.2278	-0.218	**	0.1048
CAP$_{t-1}$	-2.117	***	0.5128	-0.488	***	0.0530
DEP$_{t-1}$	-1.680	***	0.6314	-0.607	***	0.0951
MP_Cyclical index$_t$	-1.040	**	0.4599	-0.200	***	0.0330
MP_Resilience_index$_t$	-0.068	*	0.0350	-0.063	**	0.0295
*MP_Cyclical index$_t$ * CAP$_{t-1}$*	3.502	***	0.5582	1.141	***	0.0188
*MP_Cyclical index$_t$ * SIZE$_{t-1}$*	0.317	**	0.1286	0.058		0.0385
*MP_Cyclical index$_t$ * LIQ$_{t-1}$*	0.103	*	0.0624	0.345	**	0.1373
*MP_Cyclical index$_t$ * DEP$_{t-1}$*	0.891	**	0.4496	0.084		0.0562
*MP_ Resilience index$_t$ * CAP$_{t-1}$*	1.357	***	0.5073	0.719	***	0.0400
*MP_ Resilience index$_t$ * SIZE$_{t-1}$*	0.019		0.0397	0.024	**	0.0114
*MP_ Resilience index$_t$ * LIQ$_{t-1}$*	0.297	*	0.1667	0.219	*	0.1274
*MP_ Resilience index$_t$ * DEP$_{t-1}$*	1.383	**	0.5877	0.238	***	0.0397
Time dummies	yes			yes		
Sample period	1990-2012			1990-2012		
Observations	20,870			20,870		
Serial correlation test[1]	0.152			0.294		
Hansen test[2]	0.738			0.141		

Notes: The database is composed of 3,177 banks headquartered in 61 countries. Robust standard errors (clustered at the bank year level) are reported. The symbols *, **, and *** represent significance levels of 10%, 5%, and 1% respectively. The coefficient for the banking crisis dummy is not reported. [1]Reports p-values for the null hypothesis that the errors in the first difference regression exhibit no second order serial correlation. [2] Reports p-values for the null hypothesis that the instruments used are not correlated with the residuals.

Table C9: Baseline regression with aggregate macroprudential index (including country*time dummies)

	Dependent variable: Annual change of the expected default frequency over a 1 year horizon (I)			(II)			Dependent variable: Annual change of the Z-score (III)			(IV)		
	Coeff		Std err	Coeff		Std err	Coeff		Std err	Coeff		Std err
Dependent variable$_{t-1}$	0.240	**	0.1187	0.253	***	0.0095	0.346	***	0.0650	0.898	***	0.1027
SIZE$_{t-1}$	-0.016	*	0.0080	-0.137	*	0.0786	-0.034	**	0.0136	-0.021	***	0.0013
LIQ$_{t-1}$	-0.045	*	0.0235	-0.255		0.4417	-0.958	**	0.4120	-0.040	*	0.0207
CAP$_{t-1}$	-0.857	*	0.4446	-1.320	**	0.5482	-0.505	**	0.2034	-0.482	***	0.0195
DEP$_{t-1}$	-0.660	**	0.3117	-0.582	*	0.3117	-0.458	***	0.1709	-0.572	*	0.3117
*MP_index$_t$*CAP $_{t-1}$*	0.824	**	0.3892				0.963	**	0.4728			
*MP_index$_t$*SIZE $_{t-1}$*	0.012	**	0.0048				0.041	*	0.0247			
*MP_index$_t$*LIQ $_{t-1}$*	0.358	**	0.1683				0.223	**	0.1067			
*MP_index$_t$*DEP $_{t-1}$*	1.290	**	0.5108				0.025	**	0.0124			
*MP_Cyclical index$_t$ * CAP$_{t-1}$*				0.659	***	0.1603				0.144	***	0.0049
*MP_Cyclical index$_t$ * SIZE$_{t-1}$*				0.057	**	0.0226				0.005		0.0047
*MP_Cyclical index$_t$ * LIQ$_{t-1}$*				0.287		0.2443				0.033	***	0.0100
*MP_Cyclical index$_t$ * DEP$_{t-1}$*				0.516	***	0.0010				0.175	***	0.0047
*MP_ Resilience index$_t$ * CAP$_{t-1}$*				3.362	***	1.1490				0.595	***	0.0407
*MP_ Resilience index$_t$ * SIZE$_{t-1}$*				0.090	*	0.0525				0.005		0.0068
*MP_ Resilience index$_t$ * LIQ$_{t-1}$*				0.120		0.2813				0.141		0.0954
*MP_ Resilience index$_t$ * DEP$_{t-1}$*				2.267	***	0.8440				0.380	***	0.0549
Country*Time dummies	yes			yes			yes			yes		
Sample period	1990-2012			1990-2012			1990-2012			1990-2012		
Observations	20,870			20,870			20,870			20,870		
Serial correlation test[1]	0.077			0.094			0.194			0.0754		
Hansen test[2]	0.138			0.229			0.123			0.329		

Notes: The database is composed of 3,177 banks headquartered in 61 countries. Robust standard errors (clustered at the bank-year level) are reported. The symbols *, **, and *** represent significance levels of 10%, 5%, and 1% respectively. The coefficient for the banking crisis dummy is not reported. [1] Reports p-values for the null hypothesis that the errors in the first difference regression exhibit no second order serial correlation. [2] Reports p-values for the null hypothesis that the instruments used are not correlated with the residuals.

Table C10: Baseline regression with aggregate macroprudential index (controlling for regulatory strength)

	Dependent variable: Annual change of the expected default frequency over a 1 year horizon						Dependent variable: Annual change of the Z-score					
	(I)			(II)			(III)			(IV)		
	Coeff		Std err	Coeff		Std err	Coeff		Std err	Coeff		Std err
Dependent variable$_{t-1}$	0.238	***	0.006	0.244	***	0.005	0.894	***	0.028	0.912	***	0.018
ΔEDF_NFS$_t$	0.445	***	0.073	0.491	***	0.125	0.015	***	0.003	0.020	***	0.002
DIFF$_t$	-0.022	**	0.009	-0.020	**	0.009	-0.007	**	0.003	-0.010	**	0.004
ΔGDP$_t$	-0.355		0.858	-1.374		0.928	-0.696	***	0.039	-0.655	***	0.039
SIZE$_{t-1}$	-0.019	***	0.005	-0.039	**	0.019	-0.019	**	0.009	-0.012	**	0.005
LIQ$_{t-1}$	-0.123	***	0.016	-0.129	**	0.059	-0.035		0.042	-0.060	*	0.032
CAP$_{t-1}$	-0.420	***	0.139	-0.572	***	0.218	-0.765	***	0.024	-0.401	***	0.014
DEP$_{t-1}$	-0.224	**	0.092	-0.277	**	0.127	-0.873	***	0.199	-0.545	***	0.069
MP_index$_t$	-0.659	***	0.062	-0.810	***	0.245	-0.015	***	0.003	-0.022	***	0.005
*MP_index$_t$*CAP$_{t-1}$*				1.246	***	0.060				0.169	***	0.003
*MP_index$_t$*SIZE$_{t-1}$*				0.157	***	0.031				0.008	**	0.004
*MP_index$_t$*LIQ$_{t-1}$*				0.332	*	0.178				0.218	*	0.112
*MP_index$_t$*DEP$_{t-1}$*				0.247	*	0.127				0.118	***	0.015
Banking crisis index	0.283	**	0.1108	0.224	*	0.1241	0.294	**	0.120	0.291	**	0.146
Regulat. strength index	-2.804	***	0.3459	-1.641	***	0.2360	-0.574	***	0.180	-0.173	*	0.099
Sample period	1999-2012			1999-2012			1999-2012			1999-2012		
Observations	16,615			16,615			16,615			16,615		
Serial correlation test[1]	0.109			0.116			0.112			0.136		
Hansen test[2]	0.426			0.443			0.164			0.118		

Notes: The database is composed of 3,177 banks headquartered in 61 countries. Robust standard errors (clustered at the bank-year level) are reported. The symbols *, **, and *** represent significance levels of 10%, 5%, and 1% respectively. [1] Reports p-values for the null hypothesis that the errors in the first difference regression exhibit no second order serial correlation. [2] Reports p-values for the null hypothesis that the instruments used are not correlated with the residuals.

Table C11: Cyclical vs Resilience macroprudential tools (controlling for regulatory strength)

	Dependent variable: Annual change of the expected default frequency over a 1 year horizon (I)			Dependent variable: Annual change of the Z-score (II)		
	Coeff		Std err	Coeff		Std err
Dependent variable$_{t-1}$	0.089	**	0.043	0.890	***	0.067
ΔEDF_NFS$_t$	0.614	***	0.090	0.032	***	0.005
DIFF$_t$	-0.041	**	0.019	-0.018	***	0.004
ΔGDP$_t$	-1.517		2.442	-0.768	***	0.261
SIZE$_{t-1}$	-0.053	*	0.027	-0.012	**	0.005
LIQ$_{t-1}$	-0.278	***	0.015	-0.158	***	0.060
CAP$_{t-1}$	-1.711	***	0.507	-0.425	***	0.112
DEP$_{t-1}$	-1.299	***	0.192	-0.547	***	0.100
MP_Cyclical index$_t$	-0.473	**	0.194	-0.037	*	0.020
MP_Resilience_index$_t$	-0.158	***	0.042	-0.066	***	0.001
*MP_Cyclical index$_t$ * CAP$_{t-1}$*	1.510	***	0.434	0.568	***	0.145
*MP_Cyclical index$_t$ * SIZE$_{t-1}$*	0.125	*	0.067	0.009	*	0.005
*MP_Cyclical index$_t$ * LIQ$_{t-1}$*	0.551	***	0.010	0.162	***	0.040
*MP_Cyclical index$_t$ * DEP$_{t-1}$*	0.545	**	0.237	0.117	*	0.069
*MP_ Resilience index$_t$ * CAP$_{t-1}$*	2.056	**	0.913	0.621	***	0.183
*MP_ Resilience index$_t$ * SIZE$_{t-1}$*	0.088	**	0.035	0.031	***	0.006
*MP_ Resilience index$_t$ * LIQ$_{t-1}$*	0.304	*	0.158	0.104	*	0.058
*MP_ Resilience index$_t$ * DEP$_{t-1}$*	1.501	**	0.737	0.101	***	0.020
Banking crisis index	0.089	**	0.043	0.890	***	0.067
Regulatory strength index	0.614	***	0.090	0.032	***	0.005
Sample period	1999-2012			1999-2012		
Observations	16,615			16,615		
Serial correlation test[1]	0.152			0.274		
Hansen test[2]	0.738			0.741		

Notes: The database is composed of 3,177 banks headquartered in 61 countries. Robust standard errors (clustered at the bank year level) are reported. The symbols *, **, and *** represent significance levels of 10%, 5%, and 1% respectively. [1]Reports p-values for the null hypothesis that the errors in the first difference regression exhibit no second order serial correlation. [2] Reports p-values for the null hypothesis that the instruments used are not correlated with the residuals.

Table C12: Using only Z-score as dependent variable to enlarge the sample

	Baseline regression with aggregate macroprudential index			Cyclical vs Resilience macroprudential tools		
Dependent variable: Annual change of the Z-score	(I)			(II)		
	Coeff		Std err	Coeff		Std err
Dependent variable$_{t-1}$	0.921	***	0.0140	0.901	***	0.0359
ΔEDF_NFS$_t$	0.017	***	0.0059	0.023	***	0.0004
DIFF$_t$	-0.004	**	0.0015	-0.006	***	0.0019
ΔGDP$_t$	-0.228	***	0.0254	-0.645	***	0.0254
SIZE$_{t-1}$	-0.004	***	0.0012	-0.010	*	0.0053
LIQ$_{t-1}$	-0.121	**	0.0581	-0.119	*	0.0659
CAP$_{t-1}$	-0.533	***	0.1480	-1.106	***	0.0825
DEP$_{t-1}$	-0.871	**	0.4276	-1.408	***	0.1500
MP_index$_t$	-0.019	***	0.0064			
*MP_index$_t$*CAP $_{t-1}$*	0.013	***	0.0037			
*MP_index$_t$*SIZE $_{t-1}$*	0.008	**	0.0041			
*MP_index$_t$*LIQ $_{t-1}$*	0.127		0.0828			
*MP_index$_t$*DEP $_{t-1}$*	0.112	***	0.0221			
MP_Cyclical index$_t$				-0.046	**	0.0212
MP_Resilience_index$_t$				-0.024	***	0.0052
*MP_Cyclical index$_t$ * CAP$_{t-1}$*				0.385	***	0.0376
*MP_Cyclical index$_t$ * SIZE$_{t-1}$*				0.005	**	0.0024
*MP_Cyclical index$_t$ * LIQ$_{t-1}$*				0.017		0.0275
*MP_Cyclical index$_t$ * DEP$_{t-1}$*				0.010		0.0070
*MP_ Resilience index$_t$ * CAP$_{t-1}$*				0.136	***	0.0183
*MP_ Resilience index$_t$ * SIZE$_{t-1}$*				0.011	***	0.0022
*MP_ Resilience index$_t$ * LIQ$_{t-1}$*				0.293	**	0.1430
*MP_ Resilience index$_t$ * DEP$_{t-1}$*				0.212	**	0.1068
Sample period	1990-2012			1990-2012		
Observations	115,611			115,611		
Serial correlation test[1]	0.115			0.104		
Hansen test[2]	0.133			0.129		

Notes: Robust standard errors (clustered at the bank year level) are reported. The symbols *, **, and *** represent significance levels of 10%, 5%, and 1% respectively. The coefficient for the banking crisis dummy is not reported. [1]Reports p-values for the null hypothesis that the errors in the first difference regression exhibit no second order serial correlation. [2] Reports p-values for the null hypothesis that the instruments used are not correlated with the residuals.